12-2018

Global Renewable and Nonrenewable Energy Use Impact Assessment of U.S. Manufacturing: An Integrated Cradle-to-Gate LCA and DEA Approach

Bahadir Ezici
University of New Haven

Comments

Committee members: Ridvan Gedik, Armando E. Rodriguez

THE UNIVERSITY OF NEW HAVEN

GLOBAL RENEWABLE AND NONRENEWABLE ENERGY USE IMPACT ASSESSMENT OF U.S. MANUFACTURING: AN INTEGRATED CRADLE-TO-GATE LCA AND DEA APPROACH

A THESIS

submitted in partial fulfillment

of the requirements for the degree of

MASTER OF SCIENCE IN INDUSTRIAL ENGINEERING

BY

Bahadir Ezici

University of New Haven
West Haven, Connecticut
December 2018

ACKNOWLEDGEMENT

Hard times always turn out the best and I have had hard times in my MS thesis journey, but I do appreciate everything that I learned from this experience. First of all, I feel lucky to meet Dr. Gokhan Egilmez and have him as my thesis advisor. I want to thank him for all his endless supports, expertise and directions. I wouldn't finish my thesis on time without his guidance. It was an excellent experience having a chance work with him closely. I also have to say that he is one of the few people who touched, changed, and gave me a whole new perspective in life.

I also want to express my sincere gratitude to my committee members, Dr. Ridvan Gedik and Dr. Armando E. Rodriguez who took time to contribute to my thesis with their invaluable expertise. This thesis would not have been possible completed without the contribution of my committee members. Moreover, I would like to thank all my professors at the department of Mechanical and Industrial Engineering, such as Dr. M. Ali Montazer and Dr. Nadiye O. Erdil.

Last but not the least, I am extremely indebted to my parents, Hasan Ezici and Hayriye Ezici, and to my dear sister Esra Ezici, who have been with me in all my hard hopeless times. Special and truthful thanks are given to my uncles Hasan, Huseyin, Mete and my aunts Rahsan, Ulku, Inci and Fatma who have raised me. Furthermore, I would like to take this opportunity to thank all my friends, especially Mustafa Saber and Samantha Mendence. Finally, my deepest feelings and gratitude go to my only love Busra, whose support was always with me.

ABSTRACT

In this thesis, U.S. manufacturing industries` global supply chain-linked energy use and economic output are investigated considering a total of 16 renewable and nonrenewable energy carriers. A multi-region input output (MRIO) framework is employed to conduct the global supply chain-linked energy use impact assessment. The study period was between 1995 and 2014 based on data availability. Thus, 20 MRIO models were developed. Each MRIO model consists of the 40 largest economies of the world and the rest of the world (ROW) as the 41st country. Each country's economy was structured into 35 manufacturing and service industries based on the Worth Input Output Database's (WIOD) classification. The U.S. manufacturing industries' economic output and detailed renewable and nonrenewable energy used are traced at the onsite (direct) impact and domestic and global supply chain (indirect) levels. Results indicated that food, beverages and tobacco industries were the main contributors to total economic output. Mining, quarrying, chemical and chemical products industries were identified in the second and third place, respectively, based on their total economic output percentage in 2014. Furthermore, U.S. manufacturing industries' energy use was found to be heavily dependent on nonrenewable energy sources at 95.4%. Thus, only 4.6% of the total energy use was from renewable energy sources during 1995 to 2014.

Subsequently, the renewable and nonrenewable energy use of the U.S. manufacturing activities were quantified with MRIO models. The renewable and nonrenewable energy use of industries and countries were benchmarked with Data Envelopment Analysis (DEA). The objective of benchmarking was to identify the countries and industries with the ratio of renewable energy use to the nonrenewable energy use in the global supply chains. Two benchmarking measures were proposed in the DEA phase, renewability ratio (RR) and economic-output-induced renewability ratio (E-RR). These two measures are used to conduct the benchmarking analysis on countries and industries and rank them based on the corresponding efficiency scores for every 5-year period between 1995 and 2014. High efficiency scores found for industries which use less nonrenewable energy and high renewable energy such as gas and water supply (EGW), private households with employed persons (PHEP), other community and social and personal services (OCSPS) for the RR analysis. Furthermore, the least five efficient countries were found

to be Indonesia, Russian Federation, Romania, Bulgaria and Lithuania, respectively. The RR measure was more conservative in identifying and scoring the industries and countries in terms of ratio of renewable to nonrenewable energy use. On the other hand, the E-RR approach was found to be more optimistic in terms of efficiency scores since the industries' economic output was considered in addition to the ratio of renewable to nonrenewable energy use impact.

TABLE OF CONTENTS

LIST OF TABLES

TABLE OF FIGURES

1. INTRODUCTION

Manufacturing industries are primary industries for a sustainable economic growth in a country's economy. Gross output of U.S. manufacturing industries has been growing since 2008 financial crisis with an average growth rate of %0.55 (BEA - Gross Output of United States (U.S.) Manufacturing, 2018). There are nearly 12.5 million manufacturing workers in the U.S., accounting for 8.5 % of the workforce. Since the end of the Great Recession (2008), the manufacturing industry has employed more than one million workers (Bureau of Labor Statistics et al, 2016). The continuous economic growth of manufacturing industries brings energy and natural resource requirement challenges; as well as, it increases manufacturing industries` associated environmental impacts such as, energy consumption, greenhouse gas (GHG) emissions, material and land footprint. In terms of GHG emissions, manufacturing industries contribute the third largest portion of GHG emissions, after electricity production and transportation, and account for about one-third of the total energy consumption (Niwa, 2016). In this context, energy consumption and GHG emissions are highly correlated as the energy sources tend to be more nonrenewable (Kucukvar et al., 2016). Therefore, it is clear that energy consumption is among the key environmental issues that is associated with manufacturing industries in any economy (Egilmez et al., 2013). EIA's recently released (International Energy Outlook, 2013) projects that world energy consumption will grow by 56% between 2010 and 2040, from 524 quadrillion British thermal units (Btu) to 820 quadrillion Btu. Global energy consumption is highly dependent on fossil fuels according to the data. In 2012, fossil fuels accounted for 84% of worldwide energy consumption (U.S. Energy Information Administration, 2016). The U.S. is a highly industrialized country, with the industrial sector accounting for about one-third of the total U.S. energy consumption in 2016, and fossil fuels are the largest sources of energy for electricity generation.

Unfortunately, the alarm bells started to ring based on recent reports of the Energy Information Administration 2017 outlook; about 4,015 billion kilowatt-hours (kWh) (or 4.01 trillion kWh) of electricity were generated at utility-scale facilities in the United States. About 63% of this electricity generation was from nonrenewable energy sources, fossil fuels (coal, natural gas, petroleum, and other gases). About 20%

was from nuclear energy, and about 17% was from renewable energy sources (U.S. Energy Information Administration, 2018).

Human population continues to grow, which necessitates positive economic growth to provide for a healthy and happy life across the globe. In this regard, the manufacturing industry has one of the highest employment and productivity impacts on a region or country's economy (Scott, 2015). For example, electricity has the top place in consuming energy sources; more than any other sectors in the U.S. Total electricity usage in the United States in 2017 was more than 13 times greater than electricity used in 1950. (U.S. Energy Information Administration, 2017). This increased consumption is attributed to the population and economic growth, while technological advancements are expected to reduce the energy intensity of production processes (National Academy of Sciences, National Academy of Engineering, 2009). It is possible to reduce annual energy related carbon dioxide emissions in the U.S. in 2040 by roughly 6%, based on current laws and policy. This reduction adds up to a cumulative emission savings approaching five billion metric tons, according to the (U.S. Energy Information Administration, 2013). Energy consumption is expected to increase based on historical data. A forecasting study shows that total world energy consumption is expected to rise from 575 quadrillion British thermal units (Btu) in 2015 to 736 quadrillion Btu in 2040 an increase of 28% (U.S. Energy Information Administration, 2017). This clearly indicates that energy use impacts of manufacturing activities need to be thoroughly investigated.

Therefore, studying renewable vs. nonrenewable energy use of U.S. manufacturing is important for sustainable development of the U.S. economy. The U.S. manufacturing industry would be considered as the tenth largest economy if it were considered its own country. It produces the vast majority of goods and services measured by gross domestic output (GDP) (U.S. Energy Information Administration, 2017). The choices of U.S. manufacturing industries on the usage of energy resource type (renewable or nonrenewable), will have a significant effect on global energy resource level. It is important to record the type of energy usage for U.S. manufacturing industries and their supply chain linkages with other countries in order to forecast future energy resource levels. Furthermore, this thesis studies the energy use efficiency of industries and countries to determine which are efficient and which are not.

2. LITERATURE REVIEW

2.1. Life Cycle Assessment

Sustainability assessment literature consists of predominantly three Life Cycle Assessment (LCA) approaches, including process-based life-cycle assessment (P-LCA), input-output LCA (IO LCA), and hybrid LCA (Heijungs and Suh., 2013). Life Cycle Assessment has been the predominant quantitative sustainability assessment method used by researchers for tracing social, economic, and/or environmental impacts, considering the entire life cycle of a product or service (Curran, 1996).

Process life cycle assessment (P-LCA) can be defined as categorizing the process of inputs and outputs of the product or service. For example, if we consider the production of a disposable paper plastic cup, P-LCA starts with categorizing the inputs and outputs of the cup. The inputs are raw materials used such as glue and paper, and the energy spent by the machine to give a cup its' desirable shape. Scrap paper material, waste glue, and low-quality cups become waste as an output of the process. Examples of works that use P-LCA on various processes such as food production process (Andersson and Ohlsson, 1994), milk production (Eide, 2002), cattle production (Pelletier et al., 2010) and crop production (Cellura et al., 2012).

LCA becomes a complex sustainability assessment, when we aim to trace the ripple impacts of parts, sub-parts, materials and energy used in production, but provided by the supply chain industries. For example, raw materials such as pulp, water, and dyes are used to make the paper. The industries that provide these raw materials have their own processes, which makes it a complex problem to tackle with P-LCA due to high level of data collection requirements, longer time it takes to complete the assessment, and more expensive for the researcher (Egilmez et al., 2013). To overcome the aforementioned limitations and challenges of LCA, input-output analysis (IOA) has been merged with environmental impact estimation in the literature and these models are typically defined as input output-based LCA (IO-LCA). One of the earlier models, economic input-output (EIO-LCA) developed by Carnegie Mellon University, focused on tracing the onsite and domestic supply chain impacts of products and service for the U.S. economy. Later, a number of IO-LCA approaches such as ECO LCA and multi-region input-output (MRIO) models were also proposed in the literature (Kucukvar *et al.*, 2015). Thirdly, hybrid life cycle assessment is a combination of P-CLA and IO-LCA in order to eliminate the incomplete boundaries for P-CLA Yang et al. (2017).

In the last two decades, IO-LCA applications have been widely used to study the environmental, economic, and social impacts of industrial processes at the regional or national economic scales (Park et al., 2016). The relevant literature is abundant with works that use or propose IO-LCA approaches to investigate direct and indirect (supply chain-linked) environmental, social, and economic implications of products, processes, and industries. In another work, Wiebe et al. (2012), studied the direct and indirect impact energy use and CO_2 emissions associated with production of goods or service in 53 countries, 2 regions, and 48 sectors. Pan et al. (2017) reveals the relations between energy supply and demand in order to provide optimal design for energy demand and supply. Palmer (2017) developed an environmentally extended IOA to estimate the energy flows. Wu and Chen (2017) compared China`s energy use with the rest of the world. Hamilton and Kelly (2017) studied the interactions between energy, water, and food impacts of products in their different levels of supply chains. Chen et al. (2018) investigated the regional, national, and global level of embodied energy flow network by adapting the environmentally extended input-output analysis.

Even though, IO-LCA approaches brought credible advantages in terms of tracing the direct and indirect (supply chain) impacts at the regional or national economy scopes, previous works majorly employed a single region IO-LCA approach, where domestic technology assumption was held. This creates critical limitation in terms of tracing the sustainability impacts at the global-economy scope (Park et al., 2016). Therefore, multi region input output analysis (MRIO) approaches have recently been adopted to overcome the limitations of single region IO-LCA approaches Andrew et al. (2009). Indeed, Wiedmann et al. (2011) emphasized why the MRIO analysis is so popular nowadays, by listing and discussing the advantages of the framework and suggesting future works on the model. Some of the advantages of MRIO are: it provides the ability to track the impact of international manufacturing and supply chains on multiple industries in multiple countries, it could be extended for forecasting and projection applications, and complex products and processes that have global supply chains could be more accurately studied.

In terms of the applications of MRIO, for example, Wiedmann (2009) compared the IO model to the MRIO model and analyzed works conducted on tracing consumption-based emissions and resource accounting. Lenzen et al. (2010) developed an MRIO analysis to investigate the uncertainty (standard deviations) for carbon multipliers in the UK's economy. Su and Ang (2014) traced the effects of inter-regional and international trade on carbon footprint for China. Zhang et al. (2015) divided China into seven regions and studied the energy flows within and across these regions by using MRIO. Zhang et al. (2016) investigated embodied energy transfers of China, based on geographical and time changes using the MRIO models for domestic trades for specific time series. Hong et al, (2016) accomplished research on energy use embodied in Chinese consumption and interregional trade in the construction industry within China. Xia et al, (2017) investigated coal routes and its utilization in the world using MRIO table for different type of coal species for 2011. Sun et al, (2017) studied three major regions for China and their energy embodied consumptions and contributions to development for the country. Nakanoet al., (2018) proposed MRIO analysis to investigate the next generation energy system (IONGES) related with renewable energies. Ali et al., (2018) analyzed the carbon and water footprint for Italy with MRIO framework. Zhang et al. (2013) used MRIO to reveal hidden embodied energy flows domestically and inter-regionally in China. These aforementioned works clearly indicate that MRIO analysis has been predominantly used for studying energy use and energy footprint in emerging and developed economies, considering supply chain impacts within and between various regions of the world economy. Table 1 provides a summary of relevant works that focused on carbon and energy footprint by using MRIO analysis. Carbon and energy use impacts are highly correlated to each other in many regions of the world due to the larger dependency on fossil fuels for power production. In this regard, studying energy use impacts of the growing world economies is of importance, and is just as critical as addressing climate change impacts though carbon footprint analysis.

Table 1. Summary of IO-based Energy Footprint Assessment Works

	Study	Focus	Scope	Method
1	Wiedmann (2009)	CO2, energy, GHG	Survey	IO & MRIO
2	Andrew et al. (2009)	Carbon	87 Countries	MRIO
3	Lenzen et al. (2010)	CO2	UK	MRIO
4	Kanemoto et al. (2011)	N/A	187 Countries	MRIO
5	Wiedmann et al. (2011)	N/A	Methods	MRIO
6	Wiebe et al. (2012)	Energy & Carbon	53 Countries, 2 Regions, 48 sectors	MRIO
7	Zhang et al. (2013)	Energy	China	IO-MRIO
8	Su and Ang (2014)	Carbon	China	MRIO
9	Lindner and Guan (2014)	Carbon	China	(EIOA) Environmentally extended input-output analysis
10	Y. Zhang et al. (2015)	Energy	China	MRIO
11	Rocco and Colombo (2016)	Energy	Global	IO-MRIO
12	Kadhim (2016)	Carbon and Energy	41 Countries	MRIO
13	Honget al. (2016)	Energy	China	MRIO
14	Hong et al. (2016)	CO2	Australia	MRIO
15	Chen et al. (2017)	Coal	187 Countries	MRIO
16	Wu and Chen (2017)	Energy	China	IO
17	Palmer (2017)	Energy	Australia	EE-IO
18	Pan et al. (2017)	Energy	China	IO
19	Hamilton and Kelly (2017)	CO2	Sub-Saharan Africa	IO
20	Sun et al. (2017)	Energy	China	MRIO
21	Owen et al. (2018)	Energy-Water	UK	IO & MRIO
22	Nakano et al. (2018)	Energy	Japan	MRIO
23	Chen et al. (2018)	Energy	Global	EEIOA
24	Ali et al. (2018)	CO2	Italy	MRIO

The U.S. economy has been among the most economically sustainable and powerful countries, which also influences global economic policy making and trade. In this regard, like any country, manufacturing industries play a critical role for the U.S. economic output growth. While providing enormous benefits to the economy and society with employment, manufacturing industries are also responsible for considerable amount of environmental impacts, specifically greenhouse gas (GHG) emissions and energy use (Kucukvar *et al.*, 2016; Egilmez et al., 2017). Recent reports also indicate that energy use by residential and private industries is among the top drivers of the overall energy and carbon footprint in the U.S (U.S. Energy Information Administration, 2017). In this context, the majority of the relevant literature has addressed the economic and environmental impacts of U.S. manufacturing by using single-region IO-LCA models such as Egilmez et al. (2013), Egilmez and Park (2014), Park et al, (2015), Egilmez and Park (2014), Park et al. (2016), Egilmez et al. (2017).

In a recent study, Abbod (2016) investigated the multi-region carbon and energy use impacts of the U.S. manufacturing industry from a stochastic MRIO perspective, where the energy use was an aggregation of all renewable and nonrenewable energy sources. While this work addresses the energy use impacts of U.S. manufacturing economic output in the global supply chains, the energy use was traced as a whole, and no specific attention was paid to the specific renewable and nonrenewable energy carriers. And, it is crucial to study the renewable and nonrenewable energy use impacts in detail, which is the primary focus of this thesis.

2.2. Eco-Efficiency Assessment with Data Envelopment Analysis (DEA)

Manufacturing industries use both nonrenewable and renewable energy sources to carry out their operations and produce final products to other industries and customers. In this regard, eco-efficiency concept has been widely used to assess the specific industries, products, or service economic contribution in comparison to their associated environmental impacts. Eco-efficiency is termed as the ratio of the economic benefits of a DMU's activity to the environmental impacts of the corresponding activity (Egilmez et al., 2013). Among the quantitative approaches, Data Envelopment Analysis (DEA) is widely used for eco-efficiency analysis

(Huppes and Ishikawa, 2005) due to being a robust linear programming-based benchmarking approach. DEA is typically used to compare performance of Decision-Making Units (DMUs) (Sembill and Dreyer, 2009). DEA has been used to compare performance of banks, hospitals, stock market companies, schools, universities, etc. (Egilmez et al., 2016a; Egilmez et al., 2016b). DMUs could be formed as countries, industries, higher institutions, and so on, where a DMU is to be benchmarked with the rest of the DMUs in the study sample. DEA experiments results in an efficiency score, typically between 0 and 1 for each DMU, which indicates a relative performance based on the ratio of outputs (produced) to inputs (used) for the production activity (Sherman and Zhu, 1997). In the literature, efficiency scores are typically obtained based on the assumption of ratio of output(s) to input(s), thus DMUs with higher output produced and less inputs used are deemed to be classified as efficient, which yields a score of 1 (Park et al. 2016).
For example, Chien and Hu. (2007) analyzed the effect of using renewable energy on technical efficiency of 45 countries for a specific time period. Park et al. (2016) integrated DEA with ecologically based life cycle assessment (Eco-LCA) and recipe to reveal the impacts related to agricultural and food production activities in U.S. Moreover, Vázquez-Rowe et al. (2012), combined LCA + DEA models to make performance analysis for grape producers in Spain, and concluded producers can increase their efficiency by reducing the material inputs (Chenel et al. 2014),

Furthermore, a number of works focused on the energy use efficiency of the countries and industries using different methodologies. For example, Miketa and Mulder, (2005), studied the energy-productivity performance of 56 countries in 10 manufacturing sectors, during the period 1971-1995. Phylipsen et al. (1997), conducted an efficiency analysis on manufacturing energy intensities among countries considering account structural differences of countries. Ramanathan, (2005) studied the energy consumption and carbon dioxide emissions of 17 countries in the Middle East and North Africa by adapting DEA to make an efficiency analysis on countries in both regions based on their energy consumption and CO2 levels. Sözen and Alp, (2009) used DEA to compare Turkey`s energy use efficiency with the European Union (EU) countries by considering the energy consumption, local pollutants and greenhouse gas emissions. Honma and Hu (2014) estimated total-factor energy efficiency (TFEE) scores of 47 regions including years 1996 through 2008 by adapting stochastic frontier analysis model. Mukherjee (2008), applied DEA to analyze energy efficiency for the aggregate manufacturing sectors.

Furthermore, Egilmez et al. (2013) used EIO-LCA to quantify the single region (domestic onsite and domestic supply chain impacts) economic output and five environmental impacts (GHG emissions, energy use, water use, toxic releases, hazardous waste generation) of U.S. manufacturing industries for a single year study period (2007). In the latter part of this work, eco-efficiency analysis was conducted by using economic output as the nominator and environmental impacts as denominator. Even though this work is the closest study to the secondary focus of this thesis, there were four major limitations of Egilmez et al. (2013), which are further investigated with this thesis.

1) The energy impacts were considered as a whole (renewable and nonrenewable), which did not let the researchers to understand the impacts by renewable and nonrenewable energy carriers.

2) Single region IO-LCA approach was used, which holds domestic technology assumption Miller and Blair (2009), thus the global supply chain impacts of U.S. manufacturing activities were neglected.

3) The study was conducted for only 2007-year data, which is quite outdated today and did not let the researchers to study the pattern of change over a longer time period.

4) The eco-efficiency analysis considers 5 environmental impacts together, which did not reveal insights about renewable vs. nonrenewable energy use.

Based on the IOA literature review, which was summarized in Table 1, studying the renewable and nonrenewable impacts of the U.S. manufacturing industries at the global scale has not been addressed. In fact, investigating the global and domestic energy use of the U.S. manufacturing activities considering the global trade-linked economic flows is of importance; because U.S. manufacturing has been in severe competition with emerging economies such as China, Canada, European Union (EU) countries. Therefore, this thesis focuses on investigating the economic output and the renewable and nonrenewable energy use impacts of the U.S. manufacturing activities over a 20-year study period. The scope of energy use involves the energy use onsite (production processes), and national (domestic) and global supply chains where the U.S. manufacturing industries are supported with raw materials, energy, and services. The secondary focus of this thesis is to investigate the efficiency of aggregated renewable energy use to aggregated nonrenewable energy use of countries and industries. The following section explains the proposed methodology in detail.

3. METHODOLOGY

In this section, the proposed MRIO and DEA approaches are explained in detail as well as the data collection and preparation. The methodology consists of the following steps depicted in Fig. 1.

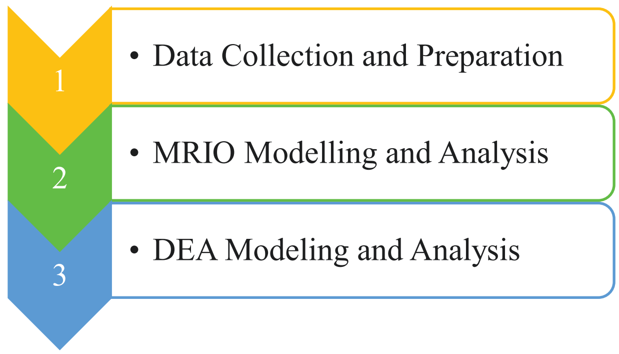

Figure 1. Hierarchical framework of the proposed methods

3.1. Data Collection and Preparation

The dataset used in this work was gathered from the World Input Output Database.(WIOD) This data covers the years from1995 to 2014; for 20 years of monetary flows among all industries, including domestic and global transactions. The study period was decided based on the available economic output and environmental impact intensity datasets that cover the longest time period, which was 20 years. Domestic transaction means the economic flow between pairs of industries (potentially within the same industry) in the same country. On the other hand, global transaction indicates the economic flows between pairs of industries, which are from different countries. The WIOD database structures the economies of the 40 countries (See Table 3) and the Rest of the World (ROW) as 35 main industries (See Table 4), which makes up (41x35=1435) 1435x1435 industry by industry structure. Codes used for these industries and countries by WIOD are represented in tables 2 and 3, respectively Dietzenbacher et al. (2013).

Energy consumption multipliers (terajoules per $M economic output) are obtained from WIOD as well. Energy use multiplier datasets consist of 16 main energy sources (carriers). These carriers are then categorized as renewable or nonrenewable energy sources and are represented in Table 2. Nuclear energy is grouped under nonrenewable energy carriers due to the consumption of uranium in its process being identified as nonrenewable by (U.S. Energy Information Administration, 2018). Energy sources vary in terms of the category such as, liquid fuels in barrels or gallons, natural gas in cubic feet, coal in short tons, and electricity in kilowatts or kilowatt-hours (U.S. Energy Information Administration, 2018). In this thesis, energy data are represented using tera-joules (TJ) and monetary flow represented by million dollars of economic activity (M$).

Table 2. Primary energy carriers in WIOD

Primary Energy Carriers	**WIOD Code**
Crude oil	Crude
Coal	HCoal, BCoal, Coke
Natural Gas	NatGas, OthGas
Nuclear Energy	Nuclear
Renewable	Waste, Biogasol, Biodiesel, Biogas, Geotherm, Solar, Wind, Othsourc, Hydro

Table 3. WIOD countries and their regional aggregation

Codes	**Country**	**Codes**	**Country**
USA	United States	ROU	Romania
CHN	China	CZE	Czech Republic
CAN	Canada	DNK	Denmark
SWE	Sweden	RUS	Russian Federation
MEX	Mexico	IRL	Ireland
IND	India	AUT	Austria
BRA	Brazil	BGR	Bulgaria
JPN	Japan	HUN	Hungary
KOR	Korea	PRT	Portugal
DEU	Germany	GRC	Greece
TWN	Taiwan	SVK	Slovakia
GBR	United Kingdom	EST	Estonia
AUS	Australia	LTU	Lithuania
IDN	Indonesia	SVN	Slovenia
FRA	France	LUX	Luxembourg
ITA	Italy	LVA	Latvia
NLD	Netherlands	CYP	Cyprus
ESP	Spain	MLT	Malta
POL	Poland	RoW	Rest of The World
BEL	Belgium		
TUR	Turkey		
FIN	Finland		

Table 4. WIOD manufacturing sectors and their abbreviations

Industry	**Abbreviations**
Agriculture, Hunting, Forestry and Fishing	AHFF
Mining and Quarrying	MQ
Food, Beverages and Tobacco	FBT
Textiles and Textile Products	TTP
Leather, Leather and Footwear	LLF
Wood and Products of Wood and Cork	WPWC
Pulp, Paper, Paper, Printing and Publishing	PPPPP
Coke, Refined Petroleum and Nuclear Fuel	CRPNF
Chemicals and Chemical Products	CCP
Rubber and Plastics	RP
Other Non-Metallic Mineral	ONMM
Basic Metals and Fabricated Metal	BMFM
Machinery, Nec	MN
Electrical and Optical Equipment	EOE
Transport Equipment	TE
Manufacturing, Nec; Recycling	MNR
Electricity, Gas and Water Supply	EGW
Construction	C
Sale, Maint. and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel	SMRMVM
Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles	WTCT
Retail Trade, Exc of Motor Vehicles and Motorcycles; Repair of Household Goods	RTEMVM
Hotels and Restaurants	HR
Inland Transport	IT
Water Transport	WT
Air Transport	AT
Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies	OSATA
Post and Telecommunications	PT
Financial Intermediation	FI
Real Estate Activities	REA
Renting of M&Eq and Other Business Activities	RMOBA
Public Admin and Defence; Compulsory Social Security	PAD
Education	E
Health and Social Work	HSW
Other Community, Social and Personal Services	OCSPS
Private Households with Employed Persons	PHEP

Furthermore, MRIO results are normalized prior to the modeling and experimentation of the proposed DEA approach. The purpose of normalizing data is eliminating the imbalance of data magnitude due to the multiple units. This normalization method is widely used in previous eco-efficiency assessment studies (Egilmez et al, 2013; Vázquez-Rowe *et al.*, 2012b; Iribarren and Vázquez-Rowe, 2013; Talluri and Paul Yoon, 2000).

3.2. The Proposed MRIO Framework

The purpose of developing MRIO models is to quantify the onsite (production), national (domestic), and global supply chain-level impacts of the U.S. manufacturing industries` economic outputs and associated nonrenewable and renewable energy use. In this regard, the longest study period between 1995 and 2014 was chosen due the data availability in WIOD database. MRIO models are developed using MATLAB software. Energy carriers are classified as renewable and nonrenewable, then evaluated by which industries are using more renewable energy versus which industries are more reliant on nonrenewable energy sources, by using MRIO results. Furthermore, DEA is adopted to make an efficiency analysis to determine which industries are more efficient than the others based on energy use of U.S. manufacturing industries on 35 main industries in 40 biggest economies and rest of the world (ROW) (See Table 2).

3.2.1. A note on the Input Output (IO) Analysis

Input-output-analysis (IOA) is a quantitative economic analysis technique that was initiated by the Wassily Leontief in the late 1930's for the purpose of tracing inter-industry flows and economic output for a regional or national economy. Since then, IOA has been widely used to estimate the economic impacts of service and production activities at the regional, national, and recently, the global economic perspectives. In the early 90's, IOA was integrated with life cycle assessment (LCA) with the objective of merging the results of IOA with environmental impact multipliers so as to quantify the environmental impacts of production and service activities. Nowadays, high speed computers and global economic output data availability have made IOA possible to study larger datasets and multiple regions of the world in a synergistic way. Thus, this made IOA a robust and computationally efficient method for economic and environmental impact assessment Miller and Blair (2009). Indeed, IOA could focus on any or every region in a state, country, or even multiple countries.

A typical IO table is depicted in Table 5 Chen et al. (2018), with arbitrary data. In simplistic terms, rows represent the producers (suppliers), and columns represent the purchasers (users). The data flow between rows versus columns are represented. Intermediate demand shows the financial flow from suppliers to users. The final demand column typically represents the consumption of final purchasers (consumers) such as government, nonprofits, private and fixed investments, and households, however, only households are considered in this example (table 5).

For instance, the agriculture industry uses $40K input from the agriculture industry in the same country, whereas the manufacturing industry uses $50K input (raw materials, subparts, etc.) from agriculture industry. The final customers (households) also purchase $80K worth of final products from the agriculture industry. Thus, the total production of agriculture industry is $40K+$50K+$80K= $170K. And, the total production and consumption in this dual-industry economy is $430K.

Table 5. Typical IO table

Country		**Transaction Table**	**Intermediate Demand**		**Final Demand**	**Total (Output)**
		(in thousands of units)	Agriculture	Manufacturing	Households	Sales (Output)
	Intermediate Producer	Agriculture	40	50	80	170
		Manufacturing	20	30	55	105
	Primary Produce	Households	110	25	20	155
		Total Purchases (inputs)	170	105	155	430

Economic integration in the global markets have been increasing rapidly in the last half-century, as different regions of the world get connected to each other more both financially and politically through globalization

(Mussa et al, 2000). Therefore, IOA that focuses on a single region (e.g. U.S. economy) would not provide sufficient results because it only considers a region and not accounting other countries and their supply chain link shares with other countries. In this regard, MRIO analysis has recently become a preferable alternative of IOA to account for the limitations of single region IOA approaches.

3.2.2. Multi Region Input Output (MRIO) Analysis

MRIO analysis eliminates shortcomings of single region IOA by taking into account the cradle-to-gate life cycle of production and service activities with an extended focus of the associated international trade links with other countries. MRIO analysis is more sensitive to the changes in the international economic policy and final demand across the regions of the global economy. In this regard, an increase in final demand of a specific industry may affect the demand on the same or other industries in the same region and/or different regions, which is typically defined as "ripple effect", like the bullwhip effect at the global scale. The case of oil extraction example is illustrated with Figure 2.The downward arrow represents demand from other regions which is called the interregional spillover effect Miller and Blair (2009). The upward arrow from Region C to B also represents interregional demand. An industry could use its own product(s) as raw material (A to A) (B to B) and (C to C) as shown in Figure 2.

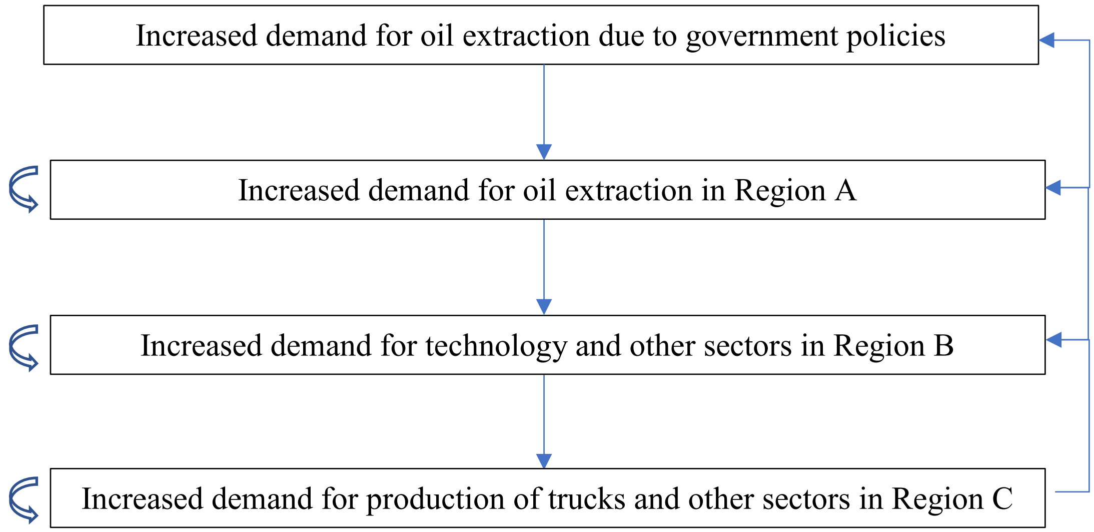

Figure 2. Increase demand on Region A affects other regions industry`s on upward direction

MRIO analysis is indeed a multi-regional extension of IOA. An example of MRIO model is shown in Table 6. Any number of industries can be classified as producer and consumer. An industry can produce and at the same time can consume its own product as finished good or raw material. MRIO mathematical model can be explained with the following example. In reality, MRIO could be extended to any number of regions and industries as long as the input-output (inter industry economic flows) data is available. Increased resolution (number of rows and columns) in the input-output tables will enable researchers to conduct more in-depth assessments that are more sensitive to the inter industry economic flows. The size of input-output table used in this study is 1435x1435, which is quite sufficient in terms of resolution and level of depth.

Table 6. MRIO Example

		Transaction Table	Intermediate Demand		Final Demand	Total (Output)
USA		(in thousands of units)	Agriculture	Manufacturing	Households	Sales (Output)
	Intermediate Suppliers	Agriculture	40	50	80	170
		Manufacturing	20	30	55	105
	Primary Supplier s	Households	110	25	20	155
		Total Purchases (inputs)	170	105	155	430
Country X		Transaction Table	**Intermediate Demand**		**Final Demand**	**Total (Output)**
		(in thousands of units)	Agriculture	Manufacturing	Households	Sales (Output)
	Intermediate Suppliers	Agriculture	15	20	50	85
		Manufacturing	30	25	45	100
	Primary Suppliers	Households	40	55	28	123
		Total Purchases (inputs)	85	100	123	308
Country Y		Transaction Table	**Intermediate Demand**		**Final Demand**	**Total (Output)**
		(in thousands of units)	Agriculture	Manufacturing	Households	Sales (Output)
	Intermediate Suppliers	Agriculture	60	43	32	135
		Manufacturing	27	19	53	99
	Primary Suppliers	Households	48	37	23	108
		Total Purchases (inputs)	135	99	108	342

A simple standard IO model, total industry output vector, x is termed as Miller and Blair, (2009):

$$x = Ax + f \tag{3.1}$$

where A is the direct requirement matrix (in other words transaction matrix), f is the final demand, and x is the total output.

X can be formulated as $x = Lf$ by using the Leontief inverse ($L = (I - A)^{-1}$) Leontief (1970). Energy use impact can be estimate after the total output is found Miller and Blair (2009).

MRIO model can be represented as in terms of the notation, equations 3.2, 3.3, and 3.4 indicate inter-industry transactions matrix, final demand vector, and total industry output vector, respectively (Kucukvar et al., 2016).

$$\boldsymbol{Z} = \begin{bmatrix} Z^{rr} & Z^{rs} & Z^{rt} \\ Z^{sr} & Z^{ss} & Z^{st} \\ Z^{tr} & Z^{ts} & Z^{tt} \end{bmatrix} \tag{3.2}$$

In equation (3.2), "**Z**" represents the monetary transaction matrix between industries.

$$\boldsymbol{f} = \begin{bmatrix} f^{r} \\ f^{s} \\ f^{t} \end{bmatrix} = \begin{bmatrix} f^{rr} + f^{rs} + f^{rt} \\ f^{sr} + f^{ss} + f^{st} \\ f^{tr} + f^{ts} + f^{tt} \end{bmatrix} \tag{3.3}$$

In equation (3.3), "**f**" represents the final demand column vector.

$$\boldsymbol{x} = \begin{bmatrix} x^{r} \\ x^{s} \\ x^{t} \end{bmatrix} \tag{3.4}$$

In equation (3.4), "x" represents the total output of industry vector.

In transaction matrix Z, economic flows between regions are depicted, which indicates the $ amount of inputs used to produce outputs ($). In ($Z_{ij}^{rs}$) economic flow from industry i in country r into industry j in country s (Eq 3.2), Furthermore, f^{rs} presents the column vector which contains the final demand values who use the output as final product such as, individuals consumptions (Eq 3.3), government consumptions and investments. Additionally, x^{r} represents the column vector of total industry outputs produced in region r (Eq 3.4). Therefore, the MRIO final mathematical formulation of total industry output (x), interindustry transaction (Z) and final demand (f) is termed as follows Miller and Blair (2009), Kucukvar et al. (2016):

$$x = Zi + f \tag{3.5}$$

where multiregional technical coefficient (A) matrix can be calculated by using Z and x. Leontief inverse function can adopt and Eq (3.5) transforms $x = Lf$ where $L = [I - A]^{-1}$ is called as Leontief inverse. One of the common usages of A matrix is also called direct requirement matrix Miller and Blair (2009):

$$A = \begin{bmatrix} A^{rr} & A^{rs} \\ A^{sr} & A^{ss} \\ A^{tr} & A^{ts} \end{bmatrix} \tag{3.6}$$

where $A^{rs} = Z^{rs}\hat{x}^{-1}$

Then, Leontief inverse (L) in other words total requirement matrix is termed as follows (Eq. 3.7 and Eq. 3.8) Miller and Blair (2009):

$$[I - A] = \begin{bmatrix} I - A^{rr} & -A^{rs} \\ -A^{sr} & I - A^{ss} \\ -A^{tr} & -A^{ts} \end{bmatrix} \tag{3.7}$$

$$L = [I - A]^{-1} = \begin{bmatrix} I - A^{rr} & -A^{rs} \\ -A^{sr} & I - A^{ss} \\ -A^{tr} & -A^{ts} \end{bmatrix}^{-1} \tag{3.8}$$

Thus, the total energy use (*y*) for a specific energy carrier could be derived as follows (Eq. 3.9), where *y* is column vector of total energy use Eq (3.9), E is a diagonal matrix of direct energy use per $ million-dollar worth of economic output (impact multiplier), and *f* is final demand.

$$y = ELf \tag{3.9}$$

Finally, the MRIO extension of the above framework is depicted as Eq (3.10)

$$y^r = E^r B^{rr} f^r + \ldots + E^{rn} B^{rnrn} + f^{rn} \tag{3.10}$$

MRIO analysis is widely used to tracking the monetary flow of industries and countries. Furthermore, environmental impacts can be calculated using MRIO analysis. Referring the above set of equations, it is possible to trace energy use of all industries across all the countries. Once the energy use impacts of U.S. manufacturing industries in the world is traced with the above described framework, results are used as the input data for DEA models and experiments. In this context, data envelopment analysis is adopted to evaluate the efficiency levels of countries and industries based on their energy use type (renewable vs. nonrenewable) and the total economic output.

3.3. Data Envelopment Analysis

Data envelopment analysis (DEA) is a linear programming-based benchmarking approach initiated by Charnels, Cooper and Rhodes (1978). In the early 1980`s, the DEA was typically used to measure only technical efficiency Westermann (1999). The analytical benchmarking approach, DEA, was mostly used for benchmarking performance of non-profit organizations. Throughout the evolution of DEA approaches and applications, the method found use in various problem domains that include benchmarking manufacturing, healthcare, government, and financial institutions Egilmez and Steward (2019). As an optimization-based benchmarking approach, DEA focuses on evaluating the efficiency of output(s) produced compared to input(s) used in multiple benchmarks, Decision-making Units (DMUs), where the most efficient DMUs would be indicated with 100% efficiency, and the others would have lower efficiency scores Sherman and Zhu (1997). Therefore, DMUs with less inputs usage and higher levels of outputs produced would stand out as "efficient." DEA identifies the most efficient DMUs as best practice units and guides the inefficient DMUs on determining the levels of reduction that need to be accomplished in the inputs and/or the levels of increase that need to be accomplished in the output(s) to become 100% efficient.

3.3.1. Mathematical Framework of DEA

DEA general input-oriented model notations are proposed by Cooper et al. (1978) and Charnes et al (1978) and indicated below:

$$max\,\theta = \frac{\sum_{r=1}^{k} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{ij}} \tag{3.11}$$

Subject to:

$$\sum_{i=1}^{m} v_i x_{io} = 1 \tag{3.12}$$

Where j is number of service units, DMU_J is service unit number j, θ is efficiency rating of the service unit being evaluated by DEA, y_{rj} is amount of output r used by service unit j, x_{ij} is amount of input i used by service unit j, i is number of inputs used by the DMU_J, r is number of outputs generated by the DMU_J, u_r is coefficient or weight assigned by DEA to output r and v_i is coefficient or weight assigned by DEA to input i.

$$DMU_1 = \frac{u_1 y_{11} + u_2 y_{12} + \cdots + u_r y_{r1}}{v_1 x_{11} + v_2 x_{21} + \cdots + v_m x_{m1}} \tag{3.13}$$

$$DMU_2 = \frac{u_1 y_{12} + u_2 y_{22} + \cdots + u_r y_{r2}}{v_1 x_{12} + v_2 x_{22} + \cdots + v_m x_{m1}} \tag{3.14}$$

$$\cdots$$

$$DMU_o = \frac{u_1 y_{1o} + u_2 y_{2o} + \cdots + u_r y_{ro}}{v_1 x_{1o} + v_2 x_{2o} + \cdots + v_m x_{mo}} \tag{3.15}$$

$$\cdots$$

$$DMU_j = \frac{u_1 y_{1j} + u_2 y_{2j} + \cdots + u_r y_{rj}}{v_1 x_{1j} + v_2 x_{2j} + \cdots + v_m x_{mj}} \tag{3.16}$$

$$u_1, \ldots, u_s \geq 0 \; and \; v_1, \ldots v_m \geq 0$$

3.3.3. Proposed DEA Approach

In this thesis, input-oriented DEA is used to conduct energy use efficiency assessment of industries and countries. Two energy use efficiency measures are proposed: Renewability ratio (RR) and ecomic-output-induced renewability ratio (E-RR).

3.3.3.1. Energy Use Efficiency Measure 1: Renewability Ratio (RR)

As discussed in the literature review, previous closest works that focused on conducting eco-efficiency analysis typically considering economic output as the output and total energy use as the input

(Egilmez et al. 2013; 2015). While these approaches provided critical insights about the total energy use impacts and its effect on eco-efficiency of manufacturing industries, the state of art has not addressed the ratio of renewable energy to nonrenewable energy use. Therefore, in this thesis, the energy use impacts were traced considering 16 energy carriers with MRIO analysis and the resulting energy use impacts data were aggregated as renewable and nonrenewable energy use for all industries and countries. Then, RR is defined as the ratio of total renewable energy use ($y^{r}_{renewable_t}$) to the total nonrenewable energy use ($y^{r}_{nonrenewable_t}$). The total energy use (both renewable and nonrenewable) data is obtained from the MRIO experiments, where the U.S. manufacturing industries' economic output's energy use impacts were traced at the local and global supply chain levels.

Following equation depicts the RR measure for industry *i*, where *i*=1…35, *c* is energy carrier (9 renewable and 7 nonrenewable energy carriers, see Table 2), in year t (between 1995 and 2014). In this equation, each industry (i) is considered to be a DMU. Furthermore, to benchmark the countries, the industries energy use is aggregated, and each country was treated as a DMU.

$$RR_{i,t} = \frac{\sum_{c=1}^{9}\sum_{r=1}^{41} y^{r}_{renewable_t}}{\sum_{c=1}^{7}\sum_{r=1}^{41} y^{r}_{nonrenewable_t}} \tag{3.17}$$

The aims of the input-oriented DEA approach are to conduct a RR efficiency analysis for 35 industries (35 DMUs are comparatively studied), and then for the 41 countries (41 DMUs are comparatively studied). The experimentations are conducted for the following years: 1995, 2000, 2005, 2010 and 2014 to study the trend of RR-efficiency change in every 5 years.

To complete the RR efficiency assessment, first renewable and nonrenewable energy use impact of the U.S. manufacturing activities were obtained from the experimental results of specific MRIO-1995, MRIO-2000, MRIO-2005, MRIO-2010, and MRIO-2014 models. It is important to note that these energy use impacts occur in all industries and countries due to the global and domestic supply chain linkages given in total requirement matrices (L). Next, the results of renewable and nonrenewable energy use are aggregated by country or by industry, depending on the objective of the assessment whether benchmarking countries or benchmarking industries, respectively. Lastly, 41 DEA models were built, and experiments were conducted for all countries to quantify the RR efficiency scores, and 35 DEA models were built and experiments were conducted for all industries to quantity the RR efficiency scores, respectively.

3.3.3.2. Energy Use Efficiency Measure 2: Economic-output-induced Renewability Ratio (ERR)

In this measure, the efficiency assessment focus is termed as Economic-output-induced Renewability Ratio (E-RR). In the first measure, only energy use impacts were considered, and the focus was on the ratio of the total renewable energy use to the total nonrenewable energy use. In this measure, economic output was added to make a more comprehensive efficiency assessment (see Eq. 3.18). Mean normalization approach was used to normalize the energy and economic output data to make sure the units of measurement and scale differences don't affect the results of experiments (Park et al., 2016).

$$ERR_i = \frac{\sum_{c=1}^{9}\sum_{r=1}^{41} y_{renewable}^{r} + \sum_{r=1}^{41} x^{r}}{\sum_{c=1}^{7}\sum_{r=1}^{41} y_{nonrenewable}^{r}} \tag{3.18}$$

4. RESULTS

The results section consists of two subsections. In the first part, MRIO results are explained. The second part introduces the DEA results.

4.1. MRIO Results

MRIO results are depicted as single year and time-series formats. As a single year, the most recent year, 2014, was used to provide insights about total economic output and energy use impacts. In the second part, time-series analysis results are provided, where the 20-year study period was focused on.

4.1.1. Analysis of MRIO-2014 Experiment

The results of MRIO-2014 model are discussed based on industry and country focus, as well as economic output and renewable vs. nonrenewable energy perspectives.

4.1.1.2 Total Economic Output of the U.S. Manufacturing Industries

The top ten U.S. manufacturing industries' total economic outputs are depicted as bar chart in fig. 3. According to the figure 3, food, beverages and tobacco industry was accounted for the highest total output with the percentage of 10.92. Mining and quarrying industry and chemical and chemical products industry was ranked as second and third, respectively.

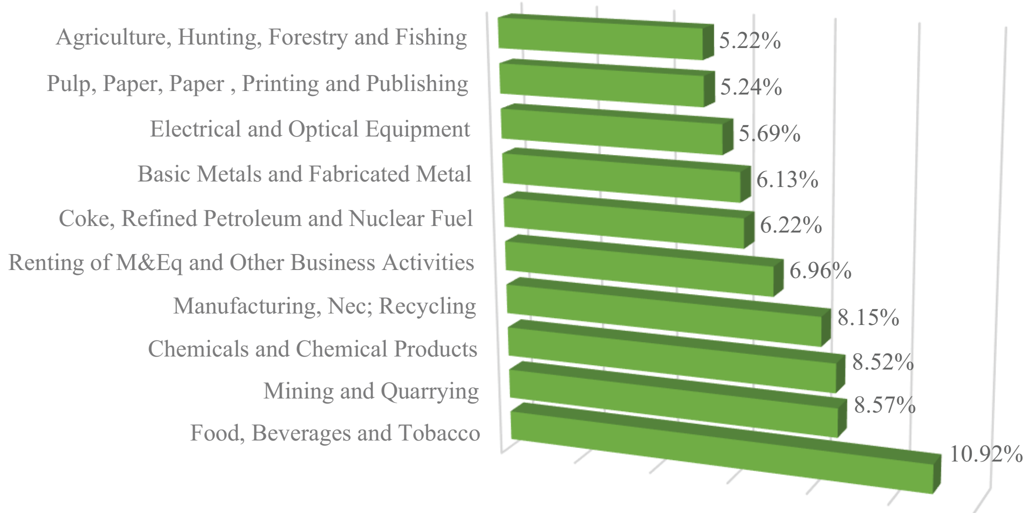

Figure 3. Top 10 U.S. Manufacturing Industries Based on Total Economic Output ($) in 2014

4.1.1.3. Energy Use Type of U.S. Manufacturing Industries

Figure 4 represents the top ten industries who used renewable energy the most in the U.S. in 2014. It also, makes a comparison between renewable vs. nonrenewable energy usage. The bar chart reveals which industries used higher levels of renewable energy and which industries are still heavily dependent on nonrenewable energy sources in year 2014. Other community, social, and personal services has the first place in the chart with 54.74% and with 45.26% of nonrenewable usage. Manufacturing, nec; recycling and construction has the second and third place based on their renewable energy usage level with the percentage of 49.99 and 46.48, respectively.

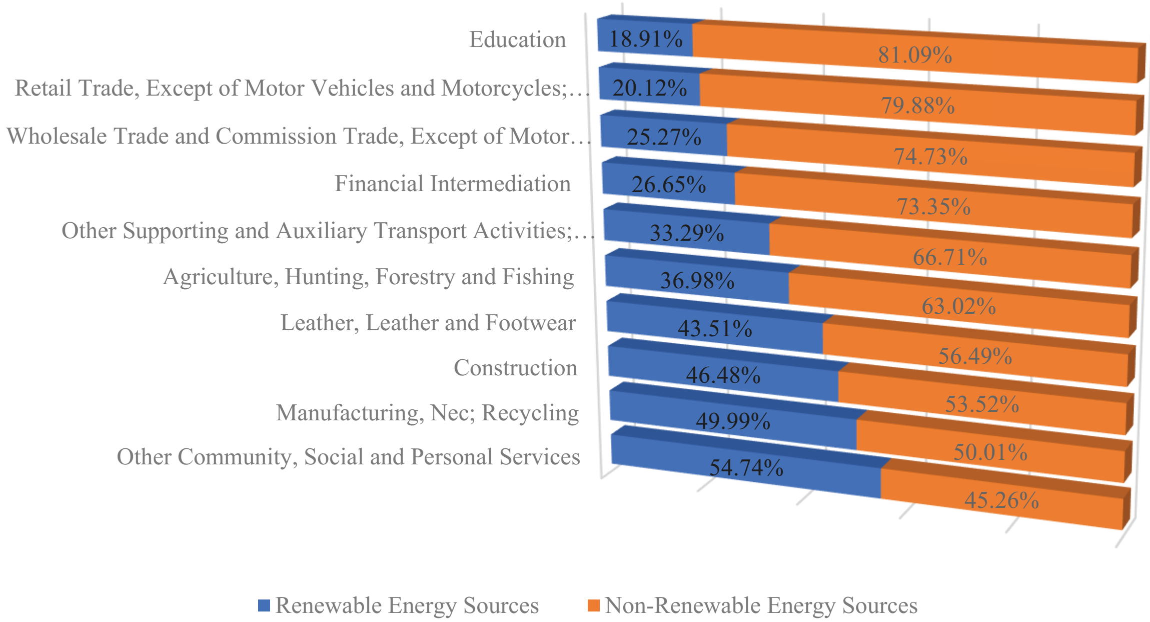

Figure 4. Renewable Energy vs Nonrenewable Energy Use (TJ) Industries in U.S. in 2014

Figure 5 represents the top 10 industries who use nonrenewable most in U.S. in 2014. It reveals which industries are still heavily dependent on nonrenewable energy sources by providing their percentage and comparing with their renewable energy usage level.

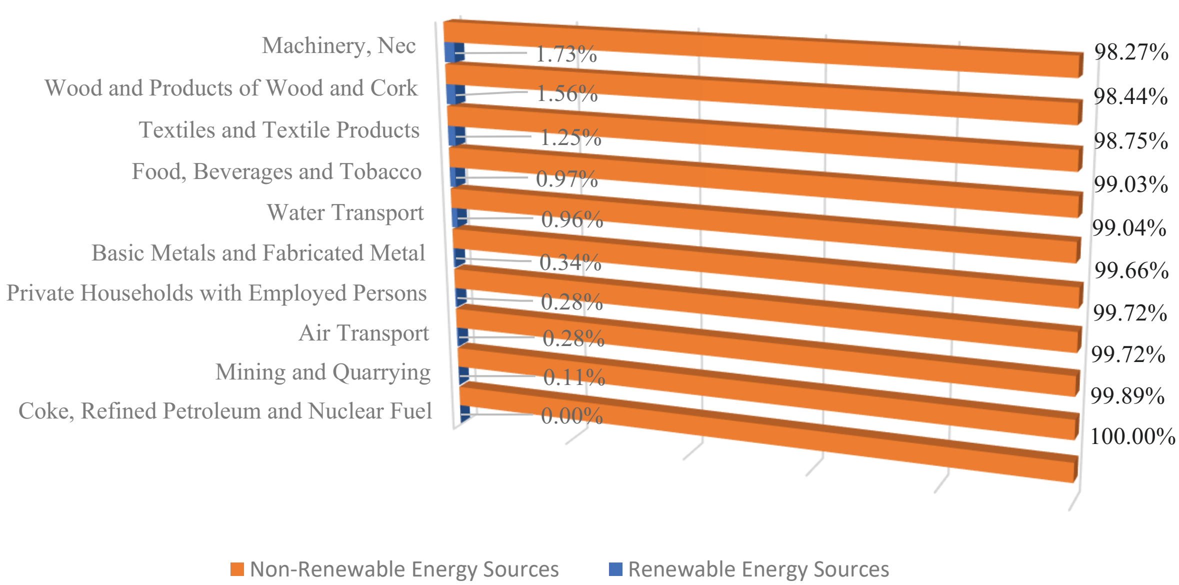

Figure 5. Nonrenewable vs Renewable Energy Use (TJ) of Industries in 2014

According to the bar chart, coke, refined petroleum and nuclear fuel is placed at the top level with the percentage of 100. It has the higher percentage which use nonrenewable energy as an input to produce its output without consuming any renewable energy. Mining and quarrying and air transport are also heavily dependent on nonrenewable energy sources. They are placed at the second and third place with the percentage of 99.89 and 99.72, respectively in 2014. Aforementioned food beverages and tobacco and mining and quarrying industries were found to have the largest total economic output producer in the U.S. in 2014 and their production is heavily dependent on nonrenewable energy sources.

4.1.1.4. Supply Chain Linkages of U.S. Manufacturing Industries Impacts on Countries

Figure 6 represents the renewable vs. nonrenewable energy use of U.S. manufacturing industries due to supply chain linkages with other countries in year 2014. The U.S. is excluded in this bar chart to identify and visualize its supply chain relations with other countries more explicitly.

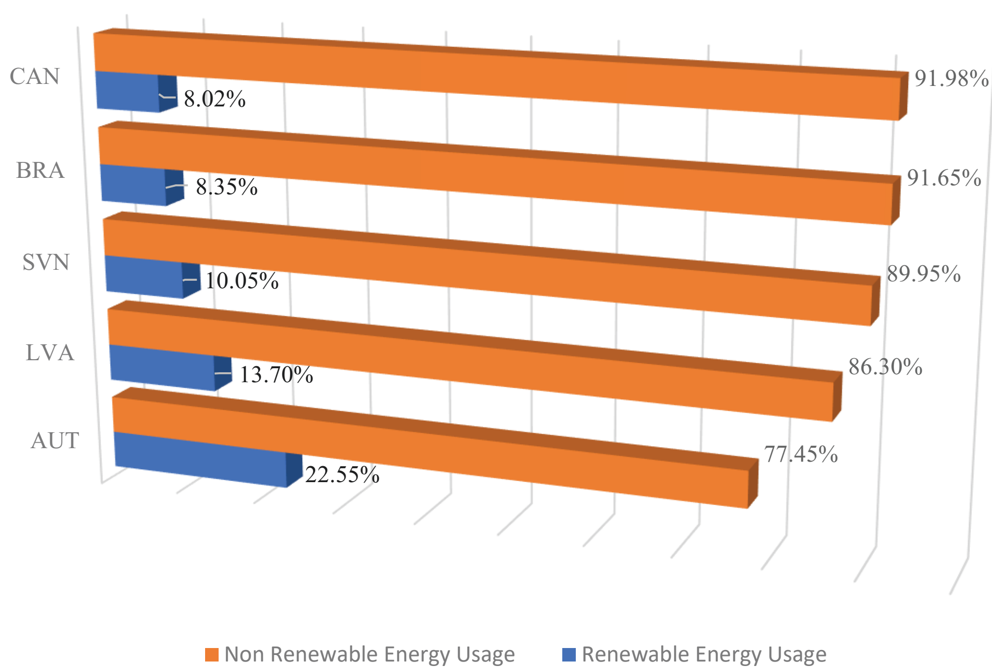

Figure 6. Renewable vs Nonrenewable Energy Use (TJ) of Top 5 Countries in 2014

According to the figure 6, U.S. manufacturing industries used the highest renewable energy for the supply chain linkages with Australia based on its renewable energy source consumption. They used 22.55% of renewable energy in order to answer Australia`s demand. Latvia and Slovenia have the second and third highest record with the percentage of 13.70% and 10.05%, respectively in 2014.

Figure 7 represents the nonrenewable vs. renewable energy use of U.S. manufacturing industries due to supply chain linkages with other countries in year 2014. U.S. is excluded in this bar chart to identify and visualize its supply chain relations with other countries more explicitly.

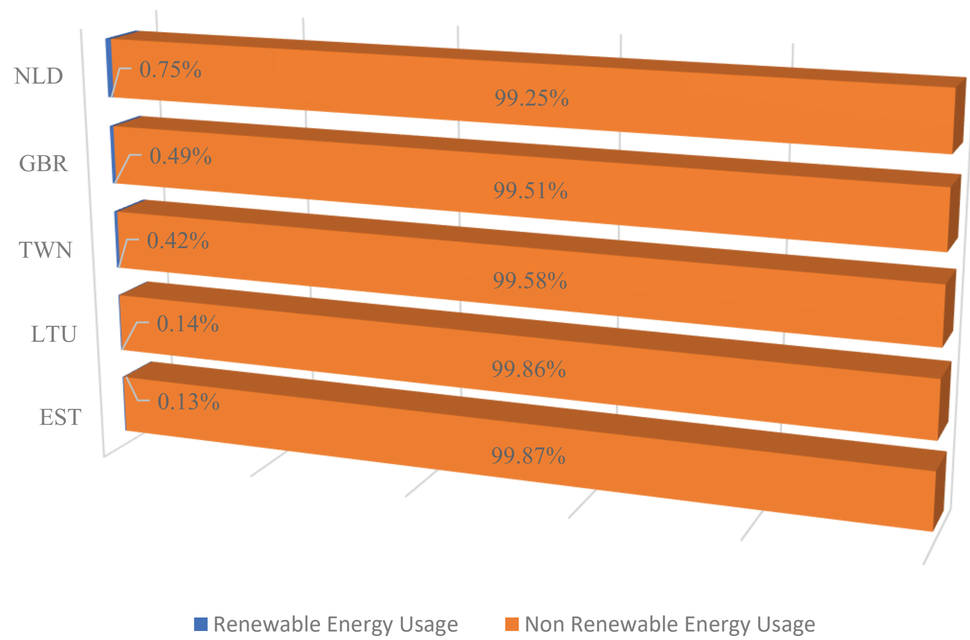

Figure 7. Nonrenewable vs Renewable Energy Use (TJ) of Countries in 2014

According to the figure 7, U.S. manufacturing industries used the highest nonrenewable energy for supply chain linkages with Estonia based on its nonrenewable energy consumption. They used 99.87% of nonrenewable energy to answer Estonia`s demand. Lithuania and Taiwan have the second and third highest record respectively, based on U.S. manufacturing industries energy use type with the percentage of 99.86% and 99.58% in 2014.

4.1.1.5. U.S. Manufacturing Industry` Impact on Domestic and Global Economic Output

Figure 8 shows the related total economic output levels of U.S. manufacturing industries (onsite and domestic supply chains) vs global in 2014.

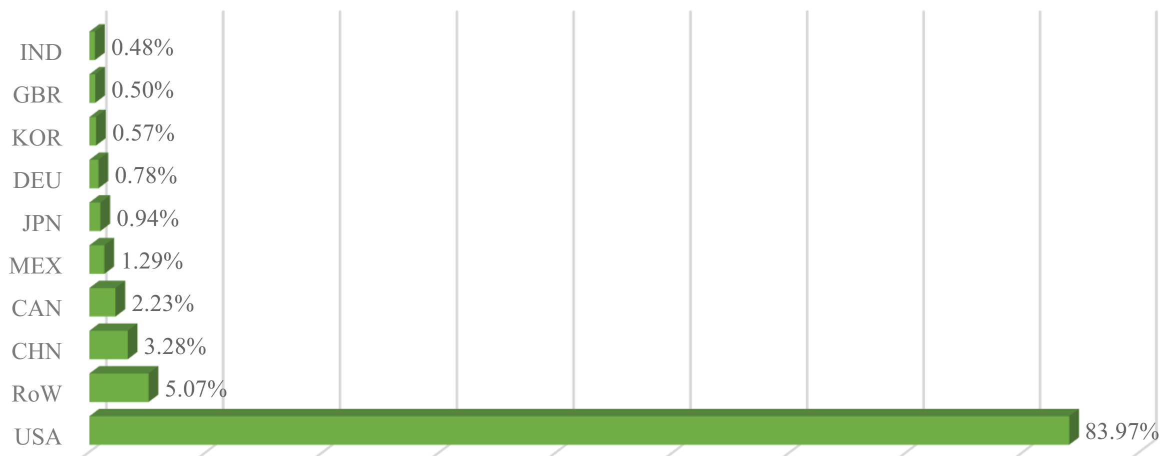

Figure 8. Global Total Economic Output ($) Due to U.S. Manufacturing Industry Activities in 2014

According to the figure 8, U.S. manufacturing industries has greatest supply chain linkages within the U.S. economy including both manufacturing and service industries, with the total economic output share of 83.97%. On the other hand, second and third greatest interaction with RoW (rest of the world) and China with the percentage of 5.07 and 3.28, respectively in 2014. Since, China manufacturing was not studied directly, and the retail industry in the U.S. was, as a service industry, not directly considered as part of the focus, the results are highly reliant on the U.S. domestic economy in terms of economic output of the U.S. manufacturing activities. As an example, both China manufacturing and retail service industries in the U.S. and in other countries were considered in the model as the suppliers of the U.S. manufacturing industries.

4.1.2. Time Series Analysis (1995 - 2014)

The domestic (onsite and domestic supply chains) and global economic output shares (%) of the U.S. manufacturing industries are provided in Figure 10. According to the results, the total economic output of U.S. manufacturing industries increased during the study period, where the domestic (U.S. manufacturing activities and supporting supply chain industries activities in the U.S.) and global supply chains has a share of 80% to 90%, and 10% to 20%, respectively.

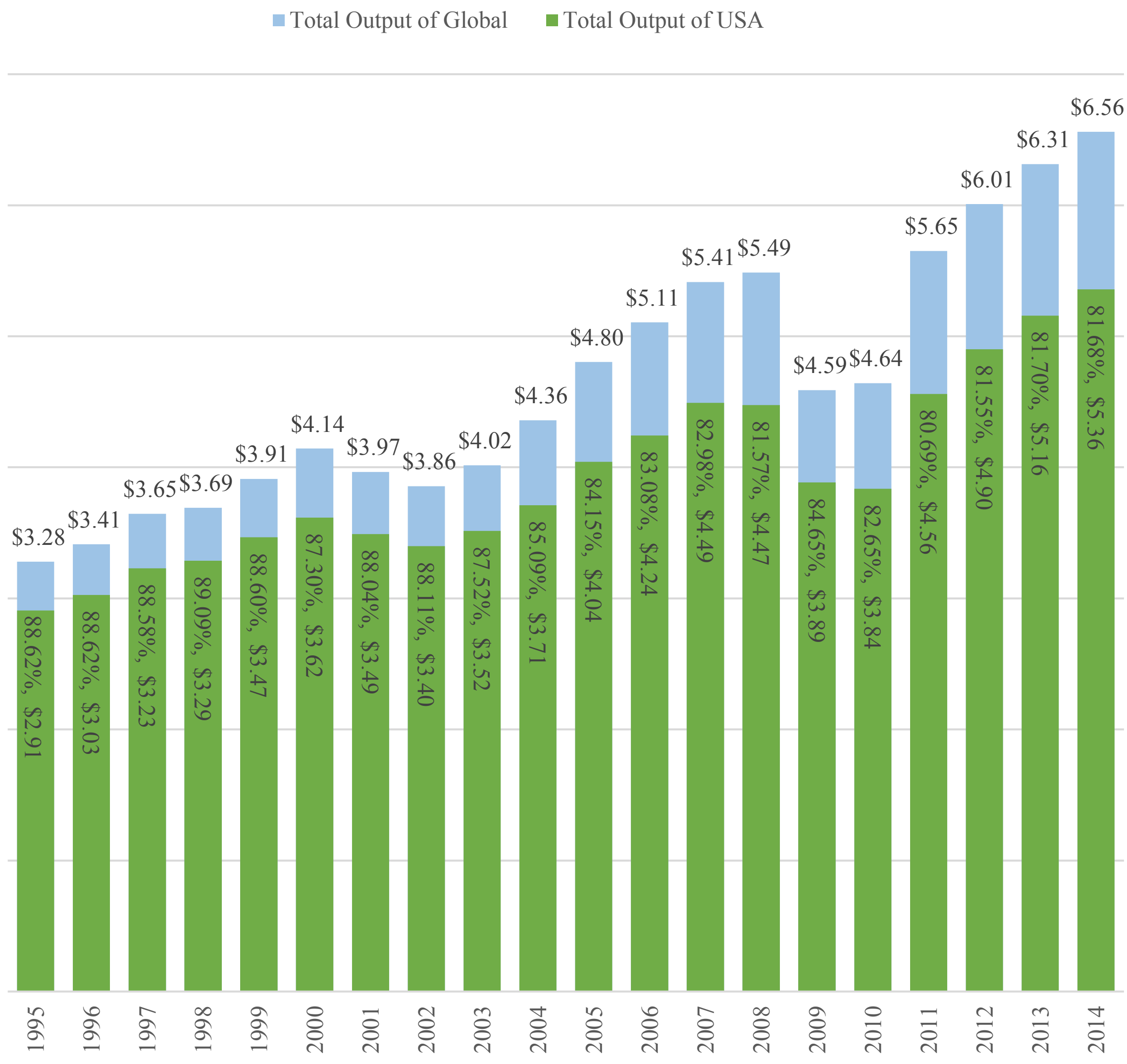

Figure 9. U.S. Domestic and Global Economic Output Shares ($) of U.S. Manufacturing Industries

The results of economic analysis (Fig. 9) show that U.S. manufacturing sectors' output has the lowest output in year 1995, controversially it has the highest share on total global output with percentage of 89. Furthermore, domestic total output share decreases gradually from 1995 to 2014, while direct economic output is increasing. This indicates that the global supply chain dependency is financially increasing. Domestic economic output average is found as $3.93 million dollars. It reaches its maximum output level in 2014 with the output level of $5.36 million dollars and minimum level in 1995 with the output level of $2.91 million dollars.

The domestic and total output levels show that similar production output behavior and their output level gradually increased until 2008. The U.S. had an economic crisis in 2008, which affected the domestic output level trend adversely and resulted in a $1 million-dollar decline between 2008 and 2009. The bar chart shows that domestic and global output level started rising up again in 2010, which also indicates the recovery trend of the manufacturing industry between 2010 and 2014.

4.1.2.1 U.S. Manufacturing Industries Energy Use

Figure 10 represents the nonrenewable energy usage of U.S. manufacturing industries due to their domestic and global supply chain linkages. The time series graph covers the years from 1995 through to 2014.

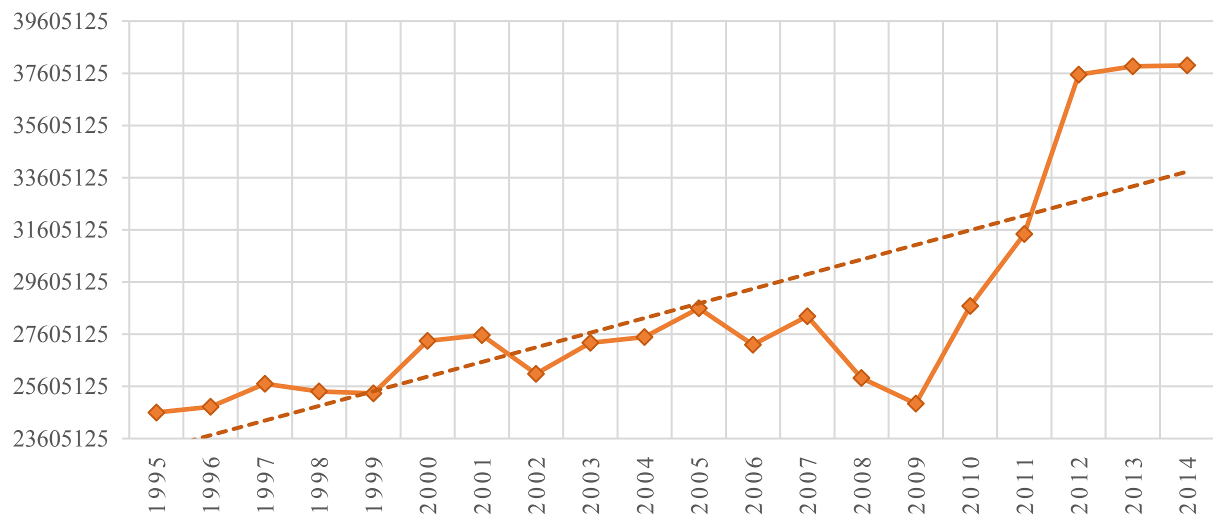

Figure 10. U.S. Manufacturing Industries Nonrenewable Energy Use (TJ) Due to It`s Supply Chain Linkages with Other Countries in Time

According to the results, the U.S. consumed the most nonrenewable energy at year 2014 with the level of 37.9 million tera joule and the lowest usage recorded at 1995 with the energy level of 24.6 million joule. In addition, the average consumption for nonrenewable energy source is recorded as 28.4 million tera joule for 20 years.

Furthermore, the chart proves the accuracy of the figure 9 (U.S. Total Economic Output vs Global Total Economic Output) by having the same pattern since the trendline should be parallel with the domestic total output. Obviously, the economic crisis in 2008 affected domestic and global output levels adversely and U.S. manufacturing industries produced less and used less energy compare to other years. Figure 11 represents the renewable energy usage of U.S. manufacturing industries due to their domestic and global supply chain linkages. The time series covers years from 1995 to 2014.

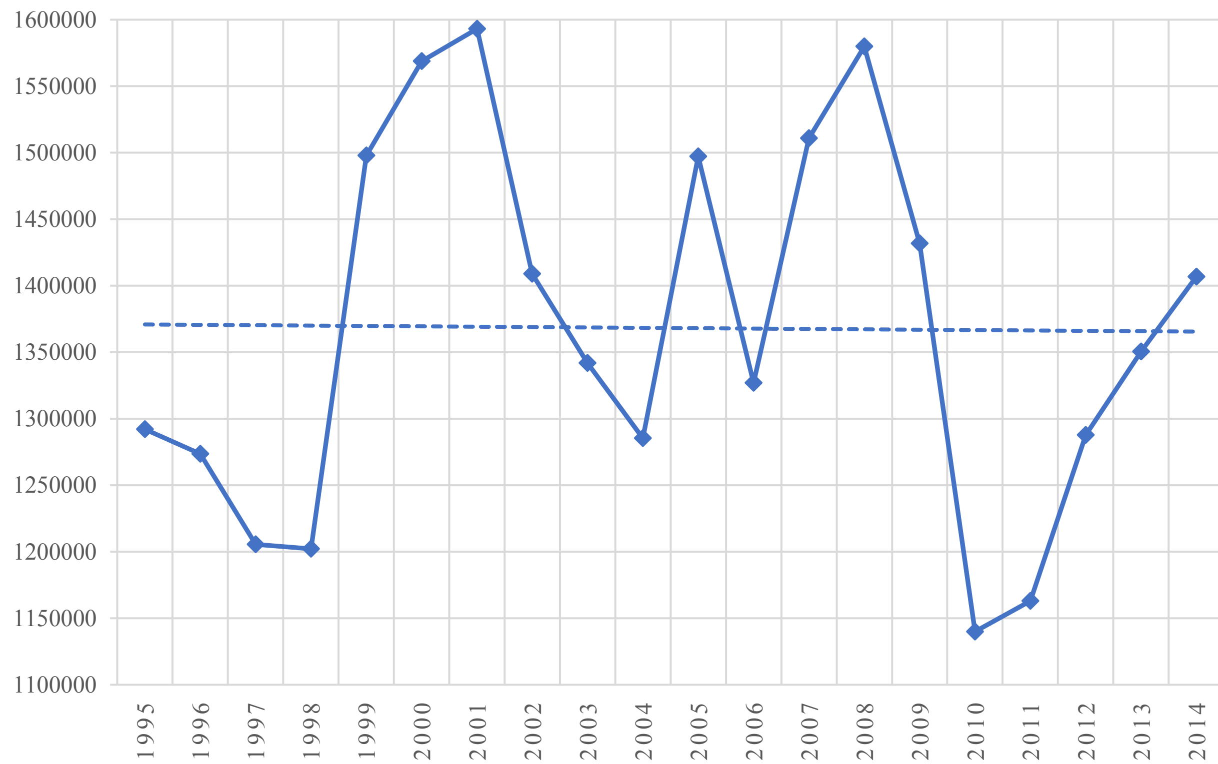

Figure 11. U.S. Manufacturing Industries Renewable Energy Use (TJ) Due to Its Supply Chain Linkages with Other Countries in Time

According to the results, U.S. manufacturing industries consumed most renewable energy at year 2001 with the level of 1.5 million tera joule and the lowest usage recorded at 2010 with the energy level of 1.1 million tera joule. In addition, the average consumption for renewable energy source is recorded as 1.3 million tera joule for 20 years.

Renewable energy usage supply chain linkages increased by 295,834 tera joule between the years 1998 to 1999 and it dropped down 66,921 tera joule and had decreased 291,765 tera joule between 2009 to 2009. Additionally, there are some up and downs on usage of renewable energy, but they are insignificant. It is important to note that final demand and government policies play a significant role on whether companies use renewable energy or not. Some policies relieve taxes on companies where they use more renewable energy for specific year (Shafiee and Topal, 2009). However, there are some mismatching that could be observed between renewable energy use and total output level graphs because U.S. manufacturing industries first choice was most times nonrenewable energy and the destiny of renewable energy usage is more dependent on more effective higher level policy making.

4.1.2.2. Specific Energy Carrier Use of U.S. Manufacturing Industries

Figure 12 shows top five energy carriers used by U.S. manufacturing industries throughout the period between 1995 and 2014. This graph is crucial in terms of revealing the fact of that energy use of U.S. manufacturing industries and their global supply chains by carrier type and % share.

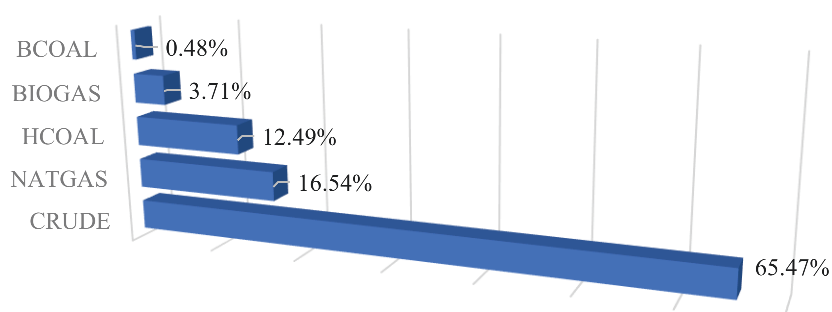

Figure 12. Top Five Energy Carriers Used by U.S. Mfg. Industries through 1995 to 2014

Crude was the energy carrier which used mostly by the U.S. manufacturing industries and their domestic and global supply chains in 20 years due to its domestic production and supply chain linkages with other countries. It is at the top place with the share of 65.47%. Unfortunately, only one renewable energy carrier was found out of the top five most used specific energy carriers. Biogas is at the fourth place as a renewable energy used by domestic manufacturing industries with the percentage of 3.71%.

Figure 13 shows top five energy carriers use in 2014. It allows making comparison with figure 12 (Top Five Energy Carriers Used by U.S. Manufacturing Industries through 1995 to 2014) to see any changes happened on U.S. manufacturing industries specific energy carrier usage.

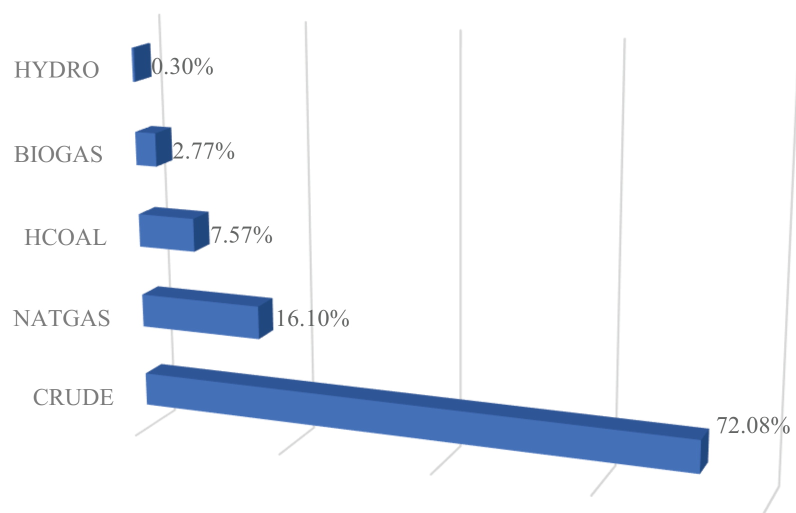

Figure 13. Top Five Energy Carriers Used by U.S. Manufacturing Industries in 2014

According to figure 13, crude is still the locomotive of U.S. manufacturing industries with the percentage of 72.08%. Natgas and hcoal consumed most after crude with the percentage level of 16.10% and 7.57%, respectively. Furthermore, hydro power placed at the fifth place as a renewable energy with the bigoas percentage of 0.30% and 2.77%, respectively. Thus, top three nonrenewable energy carriers maintained their place and hydropower joined top 5 most used energy carriers list as a renewable energy carrier. Figure 14 presents the energy use by type for the years 1995 through 2014.

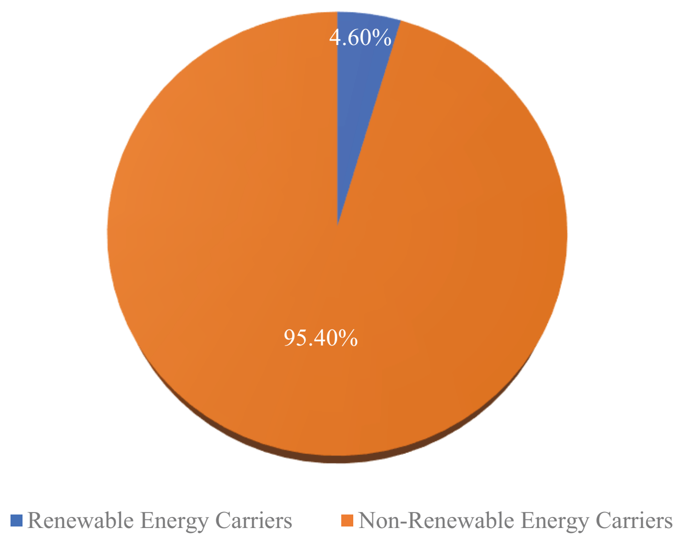

Figure 14. Energy Source Share of U.S. Manufacturing Industries in 1995 to 2014

According to the figure 14, U.S. manufacturing industries are heavily dependent on nonrenewable energy sources with the percentage of 95.40. Only 4.60% is consumed on renewable energy sources through1995 to 2014.

4.2. DEA Results

This section consists of RR and E RR analysis results respectively for industries and countries for the years 1995, 2000, 2005, 2010 and 2014.

a. In RR analysis, input is determined as nonrenewable energy use of U.S. manufacturing industries and output is determined as renewable energy use of U.S. manufacturing industries. Therefore, a country and an industry that use less nonrenewable energy at the same time high renewable energy would be ranked as the efficient DMU in RR analysis.

b. In E-RR analysis, input is determined as nonrenewable energy use of U.S. manufacturing industries and output is determined as sum of the renewable energy use of U.S. manufacturing industries and its total economic output for DEA model 2. Therefore, a country and an industry that use less nonrenewable energy at the same time high renewable energy and produce more total economic output, ranked as the efficient DMU in E-RR analysis

4.2.1. Renewability Ratio (RR) Industry Results

Changing ranking trends of RR analysis for the industries are shown in table 7 for the years 1995, 2000, 2005, 2010 and 2014. Ranking scores are ordered based on industries` efficiency scores due to their supply chain linkages with U.S. manufacturing industries.

Table 7. Industry Efficiency Ranking Results Based on RR Analysis

Years	**1995**		**2000**		**2005**		**2010**		**2014**				
Industries	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Average	Minimum	Maximum
AHFF	0.06	10	0.11	14	0.07	19	0.77	6	0.49	7	0.30	0.06	0.77
AT	0.22	6	1.00	3	1.00	4	1.00	1	1.00	2	0.84	0.22	1.00
BMFM	0.00	31	0.00	30	0.00	32	0.01	30	0.00	31	0.00	0.00	0.01
CCP	0.00	26	0.16	11	0.04	22	0.31	13	0.29	10	0.16	0.00	0.31
CRPNF	0.00	33	0.00	33	0.00	34	0.00	33	0.00	33	0.00	0.00	0.00
C	0.43	4	0.51	5	0.28	6	0.89	4	0.74	4	0.57	0.28	0.89
E	0.42	5	0.17	10	0.14	11	0.24	15	0.24	13	0.24	0.14	0.42
EOE	0.01	19	0.46	6	0.15	9	0.50	9	0.09	21	0.24	0.01	0.50
EGW	1.00	1	1.00	2	1.00	1	1.00	2	1.00	1	1.00	1.00	1.00
FI	0.09	8	0.15	12	0.15	10	0.31	12	0.30	9	0.20	0.09	0.31
FBT	0.00	29	0.00	29	0.00	31	0.01	31	0.01	30	0.01	0.00	0.01
HSW	1.00	2	0.15	13	0.08	17	0.11	21	0.11	19	0.29	0.08	1.00
HR	0.04	12	0.09	15	0.09	16	0.14	19	0.14	17	0.10	0.04	0.14
IT	0.00	30	0.00	31	0.01	30	0.02	24	0.02	24	0.01	0.00	0.02
LLF	0.00	28	0.06	21	0.06	21	0.50	8	0.65	5	0.26	0.00	0.65
MN	0.00	22	0.01	26	0.01	28	0.01	27	0.01	27	0.01	0.00	0.01
MNR	0.02	18	1.00	1	1.00	3	0.83	5	1.00	3	0.77	0.02	1.00
MQ	0.00	32	0.00	32	0.00	33	0.00	32	0.00	32	0.00	0.00	0.00
OCSPS	1.00	2	1.00	3	1.00	5	1.00	1	1.00	2	1.00	1.00	1.00
ONMM	0.00	27	0.02	24	0.02	24	0.21	17	0.02	23	0.05	0.00	0.21
OSATA	0.03	15	0.08	17	0.17	8	0.43	11	0.42	8	0.23	0.03	0.43
PT	0.06	11	0.02	23	0.02	25	0.02	25	0.02	25	0.03	0.02	0.06
PHEP	1.00	2	1.00	3	1.00	4	1.00	1	1.00	2	1.00	1.00	1.00
PAD	0.04	14	0.04	22	0.02	23	0.04	23	0.04	22	0.03	0.02	0.04
PPPPP	0.00	25	0.36	8	0.06	20	0.91	3	0.27	12	0.32	0.00	0.91
REA	0.07	9	0.22	9	0.12	12	0.11	20	0.10	20	0.12	0.07	0.22
RMOBA	0.03	16	0.08	16	0.09	13	0.70	7	0.19	15	0.22	0.03	0.70
RTEMVM	0.04	13	0.07	20	0.09	15	0.22	16	0.21	14	0.13	0.04	0.22
RP	0.01	20	1.00	4	1.00	2	0.07	22	0.13	18	0.44	0.01	1.00
SMRMVM	0.12	7	0.08	19	0.08	18	0.16	18	0.15	16	0.12	0.08	0.16
TTP	0.00	24	0.01	28	0.01	29	0.01	29	0.01	29	0.01	0.00	0.01
TE	0.00	23	0.01	25	0.01	26	0.02	26	0.02	26	0.01	0.00	0.02
WT	0.56	3	0.38	7	0.21	7	0.46	10	0.49	6	0.42	0.21	0.56
WTCT	0.02	17	0.08	18	0.09	14	0.28	14	0.28	11	0.15	0.02	0.28
WPWC	0.01	21	0.01	27	0.01	27	0.01	28	0.01	28	0.01	0.01	0.01

The average RR scores of industries for the years 1995, 2000, 2005 and 2014 is provided below. According to the results of table 8, the most efficient year is 2010 and least efficient year is 1995.

Table 8. Average RR scores

Years	1995	2000	2005	2010	2014
Average	0.18	0.27	0.23	0.35	0.30
Standard Deviation	0.32	0.36	0.36	0.36	0.34

The top 5 most efficient RR industries can be found in table 9. The results are covered averages for 5 years and minimum and maximum efficiency scores of industries in the years 1995, 2000, 2005 and 2014.

Table 9. Top 5 Most Efficient Industries Based on RR analysis

Industry	Average	Minimum	Maximum	Standard Deviation
EGW	1.00	1.00	1.00	0.00
PHEP	1.00	1.00	1.00	0.00
OCSPS	1.00	1.00	1.00	0.00
AT	0.84	0.22	1.00	0.31
MNR	0.77	0.02	1.00	0.38

According to the table 9, the most efficient industries are electricity, gas and water supply (EGW), private households with employed persons (PHEP), other community, social and personal services (OCSPS), air transport (AT), and manufacturing, nec. (MN); recycling (MNR) respectively.

The top 5 least efficient RR industries can be found in table 10. The results are covered averages for 5 years and minimum and maximum efficiency scores of industries in the years 1995, 2000, 2005 and 2014.

Table 10. Top 5 Least Efficient Industries Based on RR Analysis

Industries	Average	Minimum	Maximum	Standard Deviation
TTP	0.01	0.00	0.01	0.00
FBT	0.01	0.00	0.01	0.00
BMFM	0.00	0.00	0.01	0.00
MQ	0.00	0.00	0.00	0.00
CRPNF	0.00	0.00	0.00	0.00

According to table 10, the least efficient industries are textiles and textile products (TTP), food beverages and tobacco (FBT), basic metals and fabricated metal (BMFM), mining and quarrying (MQ) and coke, refined petroleum, and nuclear fuel (CRPNF), respectively.

4.2.2. Economic-Output-Induced Renewability Ratio (E-RR) Industry Results

Changing ranking trends of E-RR analysis for the industries are shown in table 11 for the years 1995, 2000, 2005, 2010 and 2014. Ranking scores are ordered based on industries` efficiency scores due to their supply chain linkages with U.S. manufacturing industries.

Table 11. Industry Efficiency Ranking Results Based on E-RR Analysis

Years	**1995**		**2000**		**2005**		**2010**		**2014**				
Industries	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Average	Minimum	Maximum
AHFF	1.00	2	0.95	7	0.57	7	1.00	2	1.00	3	0.90	0.57	1.00
AT	0.57	8	1.00	4	1.00	3	1.00	2	1.00	2	0.91	0.57	1.00
BMFM	0.02	25	0.01	28	0.02	26	0.34	10	0.01	28	0.08	0.01	0.34
CCP	0.02	26	0.01	29	0.02	23	0.01	30	0.08	15	0.03	0.01	0.08
CRPNF	0.00	33	0.00	35	0.00	33	0.00	32	0.00	33	0.00	0.00	0.00
C	1.00	3	0.44	9	0.46	8	0.88	6	0.71	5	0.70	0.44	1.00
E	0.47	10	0.04	22	0.02	22	0.05	19	0.05	19	0.13	0.02	0.47
EOE	0.82	7	1.00	3	1.00	1	1.00	3	0.34	11	0.83	0.34	1.00
EGW	0.00	32	0.00	34	0.00	32	0.00	33	0.00	32	0.00	0.00	0.00
FI	1.00	3	1.00	2	1.00	3	0.94	4	1.00	2	0.99	0.94	1.00
FBT	0.25	12	0.10	16	0.24	10	0.02	26	1.00	1	0.32	0.02	1.00
HSW	1.00	4	0.11	14	0.04	18	0.04	22	0.04	22	0.24	0.04	1.00
HR	0.10	19	0.06	20	0.07	16	0.06	18	0.06	17	0.07	0.06	0.10
IT	0.01	28	0.01	30	0.01	29	0.01	28	0.01	30	0.01	0.01	0.01
LLF	0.00	31	0.02	24	0.01	30	0.14	13	0.38	10	0.11	0.00	0.38
MN	0.17	14	0.14	13	0.11	15	0.10	15	0.05	21	0.11	0.05	0.17
MNR	0.16	15	0.08	18	0.13	14	0.09	16	1.00	4	0.29	0.08	1.00
MQ	0.00	29	0.01	32	0.02	24	1.00	1	0.05	18	0.22	0.00	1.00
OCSPS	0.11	18	0.11	15	0.21	11	0.19	12	0.20	13	0.16	0.11	0.21
ONMM	0.00	30	0.00	33	0.00	31	0.00	31	0.00	31	0.00	0.00	0.00
OSATA	0.12	17	0.18	12	0.33	9	0.25	11	0.26	12	0.23	0.12	0.33
PT	0.03	22	0.06	19	0.05	17	0.04	21	0.05	20	0.05	0.03	0.06
PHEP	1.00	3	1.00	6	1.00	3	1.00	2	1.00	2	1.00	1.00	1.00
PAD	0.01	27	0.01	31	0.01	27	0.02	25	0.02	26	0.02	0.01	0.02
PPPPP	0.03	24	0.04	21	0.04	19	0.04	20	0.02	25	0.04	0.02	0.04
REA	0.49	9	0.39	10	0.58	6	0.49	7	0.46	9	0.48	0.39	0.58
RMOBA	1.00	1	1.00	5	1.00	4	0.88	5	0.60	6	0.90	0.60	1.00
RTEMVM	0.14	16	0.09	17	0.14	13	0.14	14	0.15	14	0.13	0.09	0.15
RP	0.05	20	0.03	23	0.04	20	0.02	27	0.03	23	0.03	0.02	0.05
SMRMVM	0.22	13	0.02	25	0.01	28	0.03	23	0.03	24	0.06	0.01	0.22
TTP	0.04	21	0.02	26	0.02	25	0.01	29	0.01	29	0.02	0.01	0.04
TE	1.00	5	1.00	1	1.00	2	0.06	17	0.08	16	0.63	0.06	1.00
WT	0.90	6	0.38	11	0.21	12	0.46	8	0.48	8	0.49	0.21	0.90
WTCT	0.39	11	0.66	8	0.69	5	0.38	9	0.49	7	0.52	0.38	0.69
WPWC	0.03	23	0.02	27	0.02	21	0.02	24	0.02	27	0.02	0.02	0.03

The averages of E-RR of industries` efficiency scores can be found in table 12 for the years 1995, 2000, 2005 and 2014. According to table 12 results, the most efficient year is found as 2010 and 2014 having the same amount of efficiency score and least efficient year is found as 1995.

Table 12. Averages of the Years based E-RR Analysis

Years	1995	2000	2005	2010	2014
Average	0.35	0.29	0.29	0.31	0.31
Standard Deviation	0.39	0.38	0.37	0.38	0.37

The top 5 most efficient E-RR industries can be found in table 13. The results are covered averages for 5 years and minimum and maximum efficiency scores of industries in the years 1995, 2000, 2005 and 2014. According to the table 13, the most efficient industries are private households with employed persons (PHEP), financial intermediation (FT), air transport (AT), agriculture, hunting, forestry and fishing (AHFF) and renting of M&Eq and other business activities (RMOBA) respectively. The top 5 least efficient E-RR industries can be found in table 14. The results are covered averages for 5 years and minimum and maximum efficiency scores of industries in the years 1995, 2000, 2005 and 2014.

Table 13. Top 5 Most Efficient Industries Based on E-RR analysis

Industries	Average	Minimum	Maximum	Standard Deviation
PHEP	1.00	1.00	1.00	0.00
FI	0.99	0.94	1.00	0.02
AT	0.91	0.57	1.00	0.17
AHFF	0.90	0.57	1.00	0.17
RMOBA	0.90	0.60	1.00	0.16

Table 14. Top 5 Least Efficient Industries Based on E-RR Analysis

Industries	Average	Minimum	Maximum	Standard Deviation
PAD	0.02	0.01	0.02	0.01
IT	0.01	0.01	0.01	0.00
ONMM	0.00	0.00	0.00	0.00
EGW	0.00	0.00	0.00	0.00
CRPNF	0.00	0.00	0.00	0.00

According to the table 14, the least efficient industries are public admin and defense (PAD), inland transport (IT), other non-metallic mineral (ONMM), electricity, gas and water supply (EGW), and coke, refined petroleum and nuclear Fuel (CRPNF), respectively.

4.2.3. Renewability Ratio (RR) Country Results

Changing ranking trends of RR analysis for the countries are shown in table. The averages of RR of countries` efficiency scores can be found in table 15 for the years 1995, 2000, 2005 and 2014.

Table 15. Country Efficiency Ranking Results Based on RR Analysis

Years	**1995**		**2000**		**2005**		**2010**		**2014**				
Countries	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Average	Minimum	Maximum
AUS	0.03	27	0.07	33	0.07	31	0.03	35	0.04	30	0.05	0.03	0.07
AUT	1.00	2	1.00	2	1.00	1	1.00	2	1.00	2	1.00	1.00	1.00
BEL	0.01	34	0.04	37	0.09	27	0.04	34	0.04	32	0.04	0.01	0.09
BGR	0.01	35	0.09	28	0.10	25	0.05	31	0.07	26	0.06	0.01	0.10
BRA	0.89	4	0.87	4	0.93	2	1.00	3	0.92	4	0.92	0.87	1.00
CAN	1.00	3	1.00	1	0.78	4	1.00	5	1.00	1	0.96	0.78	1.00
CHN	0.14	10	0.17	19	0.17	17	0.31	13	0.31	10	0.22	0.14	0.31
CYP	0.09	17	1.00	2	0.01	38	1.00	1	1.00	2	0.62	0.01	1.00
CZE	0.01	36	0.08	31	0.07	32	0.04	33	0.05	29	0.05	0.01	0.08
DEU	0.03	28	0.09	29	0.25	13	0.43	10	0.41	7	0.24	0.03	0.43
DNK	0.08	18	0.35	11	0.66	6	0.27	15	0.25	13	0.32	0.08	0.66
ESP	0.04	25	0.10	26	0.11	23	0.07	28	0.04	31	0.07	0.04	0.11
EST	0.00	40	0.14	24	0.01	40	0.00	41	0.03	33	0.04	0.00	0.14
FIN	0.11	14	0.27	14	0.31	11	0.13	21	0.10	21	0.19	0.10	0.31
FRA	0.05	23	0.16	20	0.12	22	0.08	26	0.07	25	0.10	0.05	0.16
GBR	0.01	39	0.03	39	0.03	36	0.01	38	0.02	37	0.02	0.01	0.03
GRC	0.02	29	0.07	32	0.09	29	0.07	27	0.12	19	0.07	0.02	0.12
HUN	0.01	37	0.06	35	0.05	34	0.05	32	0.07	27	0.05	0.01	0.07
IDN	0.05	24	0.37	10	0.35	8	0.27	14	0.30	11	0.27	0.05	0.37
IND	0.07	19	0.15	22	0.17	18	0.13	22	0.13	17	0.13	0.07	0.17
IRL	0.01	33	0.09	27	0.14	19	0.17	16	0.19	14	0.12	0.01	0.19
ITA	0.11	13	0.30	13	0.30	12	0.16	19	0.11	20	0.20	0.11	0.30
JPN	0.10	15	0.17	18	0.14	20	0.12	23	0.13	18	0.13	0.10	0.17
KOR	0.02	30	0.04	36	0.05	35	0.02	37	0.03	35	0.03	0.02	0.05
LTU	0.01	38	0.10	25	0.01	39	0.00	40	0.02	36	0.03	0.00	0.10
LUX	0.06	21	0.77	6	0.23	15	0.17	17	0.36	8	0.32	0.06	0.77
LVA	0.35	6	0.87	5	0.85	3	0.46	9	1.00	2	0.70	0.35	1.00
MEX	0.42	5	0.43	9	0.34	9	0.38	11	0.35	9	0.38	0.34	0.43
MLT	1.00	2	1.00	2	0.00	41	1.00	4	1.00	2	0.80	0.00	1.00
NLD	0.02	31	0.06	34	0.06	33	0.03	36	0.03	34	0.04	0.02	0.06
POL	0.06	20	0.08	30	0.08	30	0.06	30	0.06	28	0.07	0.06	0.08
PRT	0.04	26	0.16	21	0.09	28	0.09	25	0.10	22	0.09	0.04	0.16
IDN	0.09	16	0.26	15	0.32	10	0.14	20	0.14	16	0.19	0.09	0.32
RoW	0.33	7	0.35	12	0.24	14	0.70	7	0.55	5	0.43	0.24	0.70
RUS	0.11	12	0.15	23	0.14	21	0.16	18	0.16	15	0.15	0.11	0.16
SVK	0.06	22	0.21	17	0.11	24	0.06	29	0.09	24	0.10	0.06	0.21
SVN	0.12	11	0.76	7	0.51	7	0.36	12	0.51	6	0.45	0.12	0.76
SWE	0.29	8	0.72	8	0.74	5	0.48	8	0.25	12	0.50	0.25	0.74
TUR	0.16	9	0.25	16	0.20	16	0.09	24	0.09	23	0.16	0.09	0.25
TWN	0.02	32	0.04	38	0.03	37	0.01	39	0.02	38	0.02	0.01	0.04
USA	1.00	1	1.00	3	0.09	26	1.00	6	1.00	3	0.82	0.09	1.00

Table 16. Averages of the Years based RR Analysis

Years	1995	2000	2005	2010	2014
Average	0.20	0.34	0.24	0.28	0.30
Standard Deviation	0.31	0.34	0.27	0.33	0.34

According to the results of table 16, the most efficient year is found as 2000 and least efficient year is 1995. The top 5 most efficient RR countries can be found in table 17. The results are covered averages for 5 years and minimum and maximum efficiency scores of countries in the years 1995, 2000, 2005 and 2014.

Table 17. Top 5 Most Efficient Countries Based on RR analysis

Countries	Average	Minimum	Maximum	Standard Deviation
AUT	1.00	1.00	1.00	0.00
CAN	0.96	0.78	1.00	0.09
BRA	0.92	0.87	1.00	0.04
USA	0.82	0.09	1.00	0.36
MLT	0.80	0.00	1.00	0.40

According to the table 17, the most efficient countries are Austria, Canada, Brazil, USA and Malta, respectively. Top 5 least efficient RR countries can be found in table 18. The results are covered averages for 5 years and minimum and maximum efficiency scores of countries in the years 1995, 2000, 2005 and 2014.

Table 18. Top 5 Least Efficient Industries Based on RR Analysis

Countries	Average	Minimum	Maximum	Standard Deviation
EST	0.04	0.00	0.14	0.05
KOR	0.03	0.02	0.05	0.01
LTU	0.03	0.00	0.10	0.04
TWN	0.02	0.01	0.04	0.01
GBR	0.02	0.01	0.03	0.01

According to the table 18, the least efficient countries are Estonia, Korea, Lithuania, Taiwan, and United Kingdom, respectively.

4.2.4. Economic-Output-Induced Renewability Ratio (E-ORR) Results for Countries

Changing ranking trends of E-RR analysis for the countries are shown in table 19 for the years 1995, 2000, 2005, 2010 and 2014. Ranking scores are ordered based on countries` efficiency scores due to their supply chain linkages with U.S. manufacturing industries.

Table 19. Country Efficiency Ranking Results Based on E-RR Analysis

Years	**1995**		**2000**		**2005**		**2010**		**2014**				
DMU Name	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Average	Minimum	Maximum
AUS	0.25	22	0.16	24	0.12	23	0.42	14	0.24	21	0.24	0.12	0.42
AUT	1.00	2	0.48	12	0.26	17	0.41	15	0.33	18	0.50	0.26	1.00
BEL	0.30	20	0.16	23	0.09	29	0.13	26	0.08	33	0.15	0.08	0.30
BGR	0.01	38	0.03	37	0.05	33	0.06	36	0.02	39	0.04	0.01	0.06
BRA	0.41	12	0.23	19	0.39	11	0.46	12	0.51	13	0.40	0.23	0.51
CAN	0.31	18	0.62	5	0.89	3	1.00	6	1.00	1	0.76	0.31	1.00
CHN	0.10	31	0.17	22	0.38	12	0.94	7	0.90	8	0.50	0.10	0.94
CYP	0.07	33	1.00	1	1.00	2	1.00	2	1.00	5	0.81	0.07	1.00
CZE	0.14	29	0.11	29	0.10	27	0.12	28	0.10	27	0.11	0.10	0.14
DEU	0.62	10	0.55	8	0.83	4	1.00	4	1.00	2	0.80	0.55	1.00
DNK	0.83	6	0.49	10	0.36	14	0.36	17	0.25	20	0.46	0.25	0.83
ESP	0.32	16	0.15	26	0.10	26	0.20	22	0.11	26	0.18	0.10	0.32
EST	0.00	39	0.14	27	0.16	20	0.08	34	0.01	40	0.08	0.00	0.16
FIN	0.39	14	0.23	20	0.15	21	0.14	25	0.10	29	0.20	0.10	0.39
FRA	0.65	9	0.52	9	0.68	7	0.76	10	0.61	12	0.64	0.52	0.76
GBR	0.19	25	0.55	7	0.58	8	0.39	16	0.36	15	0.41	0.19	0.58
GRC	0.17	26	0.08	34	0.12	22	0.12	27	0.09	30	0.12	0.08	0.17
HUN	0.14	28	0.13	28	0.17	19	0.19	23	0.13	25	0.15	0.13	0.19
IDN	0.13	30	0.08	33	0.05	34	0.05	37	0.05	38	0.07	0.05	0.13
IND	0.14	27	0.10	30	0.12	24	0.19	24	0.26	19	0.16	0.10	0.26
IRL	0.97	4	1.00	1	1.00	2	1.00	2	1.00	3	0.99	0.97	1.00
ITA	0.75	7	0.60	6	0.79	5	0.60	11	0.50	14	0.65	0.50	0.79
JPN	1.00	1	1.00	2	1.00	2	1.00	5	1.00	6	1.00	1.00	1.00
KOR	0.39	13	0.28	17	0.37	13	0.32	20	0.33	17	0.34	0.28	0.39
LTU	0.00	40	0.09	31	0.04	36	0.03	38	0.01	41	0.04	0.00	0.09
LUX	0.88	5	1.00	1	1.00	2	1.00	3	0.78	11	0.93	0.78	1.00
LVA	0.03	37	0.45	14	1.00	2	1.00	2	0.06	36	0.51	0.03	1.00
MEX	0.30	19	0.62	4	0.74	6	0.91	8	0.90	9	0.69	0.30	0.91
MLT	1.00	2	1.00	1	1.00	2	1.00	2	1.00	4	1.00	1.00	1.00
NLD	0.37	15	0.28	18	0.19	18	0.22	21	0.14	23	0.24	0.14	0.37
POL	0.08	32	0.09	32	0.08	30	0.10	31	0.08	31	0.09	0.08	0.10
PRT	0.21	24	0.16	25	0.11	25	0.10	30	0.08	32	0.13	0.08	0.21
ROM	0.04	35	0.04	36	0.04	35	0.10	33	0.06	37	0.06	0.04	0.10
RoW	0.31	17	0.44	15	0.50	9	0.89	9	0.82	10	0.59	0.31	0.89
RUS	0.03	36	0.02	38	0.06	32	0.10	32	0.10	28	0.06	0.02	0.10
SVK	0.05	34	0.05	35	0.09	28	0.12	29	0.07	35	0.07	0.05	0.12
SVN	0.21	23	0.32	16	0.44	10	0.44	13	0.16	22	0.31	0.16	0.44
SWE	0.72	8	0.45	13	0.32	16	0.34	19	0.13	24	0.39	0.13	0.72
TUR	0.26	21	0.18	21	0.08	31	0.07	35	0.07	34	0.13	0.07	0.26
TWN	0.56	11	0.48	11	0.35	15	0.35	18	0.35	16	0.42	0.35	0.56
USA	1.00	3	1.00	3	1.00	1	1.00	1	1.00	7	1.00	1.00	1.00

The average of E-RR of countries` efficiency scores can be found in table 20 for the years 1995, 2000, 2005 and 2014.

Table 20. Averages of the Years based E-RR Analysis

Years	1995	2000	2005	2010	2014
Average	0.37	0.38	0.41	0.46	0.38
Standard Deviation	0.32	0.31	0.35	0.37	0.37

According to the results of table 20, the most efficient year is found as 2010 and the least efficient year is 1995.

The top 5 most efficient E-RR countries can be found in table 21. The results are covered averages for 5 years and minimum and maximum efficiency scores of industries in the years 1995, 2000, 2005 and 2014

Table 21. Top 5 Most Efficient Country Based on E-RR analysis

DMU	Average	Minimum	Maximum	Standard Deviation
MLT	1.00	1.00	1.00	0.10
JPN	1.00	1.00	1.00	0.26
USA	1.00	1.00	1.00	0.08
IRL	0.99	0.97	1.00	0.02
LUX	0.93	0.78	1.00	0.09

According to the table 21, the most efficient countries are Malta, Japan, USA, Ireland and Luxembourg respectively. The top 5 least efficient E-RR countries can be found in table 22. The results are covered averages for 5 years and minimum and maximum efficiency scores of countries in the years 1995, 2000, 2005 and 2014. According to the table 22, the least efficient countries are Indonesia, Russian Federation, Romania, Bulgaria and Lithuania, respectively.

Table 22. Top 5 Least Efficient Country Based on E-RR Analysis

Countries	Average	Minimum	Maximum	Standard Deviation
IDN	0.07	0.05	0.13	0.11
RUS	0.06	0.02	0.10	0.19
ROM	0.06	0.04	0.10	0.08
BGR	0.04	0.01	0.06	0.09
LTU	0.04	0.00	0.09	0.00

5. CONCLUSIONS AND FUTURE WORK

Manufacturing industries play a significant role in domestic and global economic activities due to their multiplier impact on economic growth, employment, and supply-chains. In addition, manufacturing industries are among the primary contributors to the overall carbon footprint, thus the climate change impacts. Especially in the case of manufacturing industries, economic output and energy use are well correlated since these industries energy and material use intensity is much higher than service industries in both developed and developing parts of the world. In this regard, increasing the renewable energy use share of manufacturing industries' is a crucially important policy making area from global sustainable development perspective. While sustainable development initiatives, recently set as 17 United Nations Sustainable Development Goal 7 (UN SDG-7), indicate that lowering the energy use and intensities significantly by 2030, manufacturing industries have a substantial responsibility in realizing these goals and it will not be possible to reach the sustainable development goals for any country if the manufacturing industries energy intensity and nonrenewable energy use shares are not decreased substantially.

Therefore, this thesis investigated the U.S. manufacturing industries economic activities and resulting energy use considering renewable and nonrenewable energy carriers at the global supply chain level, which includes the onsite (domestic production activities), domestic supply chain and global supply chain impacts. To quantify the energy use and economic output, multi region input output (MRIO) analysis models were developed over a study period between 1995 and 2014. The outputs of MRIO models included total domestic and global economic output and renewable and nonrenewable energy use. In the second part of the methodology, data envelopment analysis (DEA) was employed to conduct a benchmarking analysis of industries and countries focusing on the ratio of renewable to nonrenewable energy use with/without the impact of economic output. Furthermore, industries and countries are ranked based on their efficiency scores for 1995, 2000, 2005, 2010 and 2014.

a. In our work, DEA analysis results were found to be sensitive to government policies and international trade. Aforementioned, government policies may play significant role on what to produce on which industry for a specific year Miller and Blair, (2009). Any policy making that creates a shift in renewable or nonrenewable energy use in the U.S. as well as in the countries who are supplying parts, materials, sub-parts to the U.S. manufacturing could be affected by these policy changes immediately. Indeed, for a specific year or in a given time horizon, energy policy and international trade regulations could dramatically affect the output for specific industry and country.

b. Food, beverages and tobacco industry was found to be main contributor to total economic output. Mining and quarrying and chemical and chemical products were ranked as the second and third, respectively based on their output percentage shares in year 2014. It was also found that their production is heavily dependent on nonrenewable energy sources. This clearly indicates that U.S. manufacturing energy use is not in the expected trajectory in terms of UN SDG-7.

c. The result indicated that U.S. manufacturing sectors' output had the lowest output in year 1995, controversially it had the highest share on total global output with percentage of 89. Furthermore, domestic total output share decreases gradually from 1995 to 2014, however its own output level was increasing. Domestic output average was found as $3.93 million dollars in 20 years. It reached its maximum output level in 2014 with the output level of $5.36 million dollars and minimum level in 1995 with the output level of $2.91 million dollars. The domestic and total output levels showed that similar production output behavior and their output level gradually increased until 2008. The U.S. had an economic crisis in, which affected the domestic output level trend adversely, which proved the accuracy of figure 10; the trendline goes through a $1 million-dollar downward transition between 2008 and 2009. The analysis also indicated that domestic and global output level started rising up again in 2010.

Regarding benchmarking industries and countries:

a) There were substantial fluctuations observed on RR and ERR scores of industries and countries. No clear and sustainable increase in RR or ERR was observed during the study period. ERR scores were found to be somewhat higher than RR scores to the increasing impact of economic output in an industry's or country's efficiency score. This also indicated that RR measure was more conservative measure compared to the ERR.

b) DEA provided expected results in terms of the order of efficient and least efficient industries for both RR and E-RR analyses.

    i. In RR analysis, it was predicted to have industries with high efficiency scores which used less nonrenewable energy and high renewable energy such as gas and water supply (EGW), private households with employed persons (PHEP), other community and social and personal services (OCSPS).

    ii. In RR analysis, it was found that industries which use non-renewable energy highly were to be identified as the least efficient industries, such as, textiles and textile products (TTP), food beverages and tobacco (FBT), basic metals and fabricated metal (BMFM), mining and quarrying (MQ) and coke, refined petroleum, and nuclear fuel (CRPNF).

c) DEA provided fluctuating results in terms of the order of efficient units for the countries both in RR and E-RR analysis.

    i. Forty biggest economies and RoW were considered in the DEA analysis in order to capture whole supply chain share of U.S. manufacturing industries to make an efficiency analysis. Basic DEA models were not capable to complete analysis with negative and values equal zero Charnes et al. (1991). However, the supply chain of energy share with Malta and Cyprus were inadequate (zero) so these two nations` supply chain share with U.S. manufacturing industries adjusted the smallest value in the column when their share was equal zero. In the proposed DEA experiment, for instance, Malta`s energy use and economic output share was very small. Therefore, Malta became the efficient unit based on its adjusted level.

d) Changes on the rankings and scores between RR and E-RR analyses for the both industry and country results were expected and observed, due to the effect of the total economic output changes and the analyses period being every 5-year, which is a quite long period for countries' economic and environmental policy making and alignment.

i. In E-RR analysis, higher performance scores were found in industries such as private households with employed persons (PHEP), financial intermediation (FT), air transport (AT) due to their less non-renewable energy and high renewable energy use and at the same time their total economic output levels.

e) The most and the least efficient countries were found as Austria, and United Kingdom, respectively based on RR measure. On the other hand, the most and least efficient countries were found as Malta and Lithuania, respectively based on E-RR measure.

f) Since total economic output was a positive indicator, it typically increased the efficiency score for any industry or a country.

g) The most efficient year was found as 2010 and the least efficient year found as 1995 based on the average scores of the RR industry model. This points out that renewable energy use level was low at the 1995 compared to 2014.

h) E-RR efficiency scores of countries recorded high in 2010 and 2014 because E-RR accounts for the total economic output where RR only considers renewable energy use as an output. We can conclude that U.S. manufacturing industries and global supply chains consumed more renewable energy and less nonrenewable energy at 2010 and 2014 compared to 1995.

This thesis gathered data from world input output database (WIOD) and availability of data was limited until 2014. Expanding study focus after 2014 as more data becomes available could be further studied. The focus of analysis was based on the U.S. manufacturing only. Therefore, the study focus could be extended to include and conduct a comparative analysis between other major economies such as China, Europe's manufacturing. Additionally, Malmquist DEA models could be also used to study the annual change in RR and E-RR for the study period. Furthermore, undesirable input and output model noted as the future work. Finally, mid-point and end-point impacts of energy carriers and their material-dependencies in the world also left as an important future research dimension.

6. REFERENCES

Ali, A. I., & Seiford, L. M. (1990). Translation invariance in data envelopment analysis. Operations research letters, 9(6), 403-405.

Ali, Y., Pretaroli, R., Socci, C., & Severini, F. (2018). Carbon and water footprint accounts of Italy: A Multi-Region Input-Output approach. Renewable and Sustainable Energy Reviews, 81, 1813-1824.

Andersson, K., Ohlsson, T., & Olsson, P. (1994). Life cycle assessment (LCA) of food products and production systems. Trends in Food Science & Technology, 5(5), 134-138.

Andrew, R., Peters, G. P., & Lennox, J. (2009). Approximation and regional aggregation in multi-regional input–output analysis for national carbon footprint accounting. Economic Systems Research, 21(3), 311-335.

BEA - Gross Output of U.S. Manufacturing (2018). Retrieved from https://apps.bea.gov/iTable/iTable.cfm?ReqID=51&step=1#reqid=51&step=2&isuri=1.

Bowlin, W. F. (1998). Measuring performance: An introduction to data envelopment analysis (DEA). The Journal of Cost Analysis, 15(2), 3-27.

Bureau of Labor Statistics (2016) Employment by major industry sector. Retrieved from https://www.bls.gov/emp/tables/employment-by-major-industry-sector.htm

Cellura, M., Ardente, F., & Longo, S. (2012). From the LCA of food products to the environmental assessment of protected crops districts: a case-study in the south of Italy. Journal of environmental management, 93(1), 194-208.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. European journal of operational research, 2(6), 429-444.

Charnes, A., Cooper, W. W., & Thrall, R. M. (1991). A structure for classifying and characterizing efficiency and inefficiency in data envelopment analysis. Journal of Productivity Analysis, 2(3), 197-237.

Chen, B., Li, J. S., Wu, X. F., Han, M. Y., Zeng, L., Li, Z., & Chen, G. Q. (2018). Global energy flows embodied in international trade: A combination of environmentally extended input–output analysis and complex network analysis. Applied Energy, 210, 98-107.

Lorenzo-Toja, Y., Vázquez-Rowe, I., Chenel, S., Marín-Navarro, D., Moreira, M. T., & Feijoo, G. (2015). Eco-efficiency analysis of Spanish WWTPs using the LCA+ DEA method. Water research, 68, 651-666.

Chien, T., & Hu, J. L. (2007). Renewable energy and macroeconomic efficiency of OECD and non-OECD economies. Energy Policy, 35(7), 3606-3615.

Curran, M.A., (1996). Environmental Life-Cycle Assessment, New York, NY: MCGraw-Hill

Dietzenbacher, E., Los, B., Stehrer, R., Timmer, M., & De Vries, G. (2013). The construction of world input–output tables in the WIOD project. Economic Systems Research, 25(1), 71-98.

Egilmez, G., Kucukvar, M., Tatari, O., & Bhutta, M. K. S. (2014). Supply chain sustainability assessment of the US food manufacturing sectors: a life cycle-based frontier approach. Resources, Conservation and Recycling, 82, 8-20.

Egilmez, G., Bhutta, K., Erenay, B., Park, Y. S., & Gedik, R. (2017). Carbon footprint stock analysis of US manufacturing: a time series input-output LCA. Industrial Management & Data Systems, 117(5), 853-872.

Egilmez, G., Kucukvar, M., & Park, Y. S. (2016). Mode-specific eco-efficiency analysis of the freight transportation in the USA: an integrated life cycle assessment and linear programming approach. World Review of Intermodal Transportation Research, 6(1), 16-42.

Egilmez, G., Kucukvar, M., & Park, Y. S. (2016). Supply chain-linked sustainability assessment of the US manufacturing: an ecosystem perspective. Sustainable Production and Consumption, 5, 65-81.

Egilmez, G., Kucukvar, M., & Tatari, O. (2013). Sustainability assessment of US manufacturing sectors: an economic input output-based frontier approach. Journal of Cleaner Production, 53, 91-102.

Egilmez, G., & Park, Y. S. (2014). Transportation related carbon, energy and water footprint analysis of US manufacturing: An eco-efficiency assessment. Transportation Research Part D: Transport and

Environment, 32, 143-159.

Egilmez, G. and Steward, S. (2019) 'Food Security Performance Assessment of the U.S. States: A DEA-Based Malmquist Productivity Index Approach', International Journal of Agricultural Resources, Governance and Ecology, p. (Accepted).

EIA (2013) Extending current energy policies would reduce U.S. energy use, carbon dioxide emissions. Retrieved from https://www.eia.gov/todayinenergy/detail.php?id=11051.acc

Eide, M. H. (2002). Life cycle assessment (LCA) of industrial milk production. The International Journal of Life Cycle Assessment, 7(2), 115.

Egilmez, G., Mohamed Abdul Ghani, N. M. A., & Gedik, R. (2017). Layer analysis of CO2 sources in the US economic supply chains: an input output LCA study. Industrial Management & Data Systems, 117(10), 2171-2193.

Hamilton, T. G. A., & Kelly, S. (2017). Low carbon energy scenarios for sub-Saharan Africa: An input-output analysis on the effects of universal energy access and economic growth. Energy Policy, 105, 303-319.

Heijungs, R. & S. S. (2013) Eco-Efficiency in Industry and Science, Springer Science Business Media Dordrecht. Vol.11 doi: 10.1007/978-94-010-0197-7.

Hong, J., Shen, G. Q., Guo, S., Xue, F., & Zheng, W. (2016). Energy use embodied in China′ s construction industry: a multi-regional input–output analysis. Renewable and Sustainable Energy Reviews, 53, 1303-1312.

Honma, S., & Hu, J. L. (2014). A panel data parametric frontier technique for measuring total-factor energy efficiency: An application to Japanese regions. Energy, 78, 732-739.

Huppes, G., & Ishikawa, M. (2005). Eco-efficiency and Its xsTerminology. Journal of Industrial ecology, 9(4), 43-46.

Iribarren, D., & Vázquez-Rowe, I. (2013). Is labor a suitable input in LCA+ DEA studies? Insights on the combined use of economic, environmental and social parameters. Social Sciences, 2(3), 114-130.

Kucukvar, M., Egilmez, G., Onat, N. C., & Samadi, H. (2015). A global, scope-based carbon footprint modeling for effective carbon reduction policies: Lessons from the Turkish manufacturing. Sustainable Production and Consumption, 1, 47-66.

Kucukvar, M., Cansev, B., Egilmez, G., Onat, N. C., & Samadi, H. (2016). Energy-climate-manufacturing nexus: New insights from the regional and global supply chains of manufacturing industries. Applied energy, 184, 889-904.

Lenzen, M., Wood, R., & Wiedmann, T. (2010). Uncertainty analysis for multi-region input–output models–a case study of the UK's carbon footprint. Economic Systems Research, 22(1), 43-63.

Leontief, W. (1970). Environmental repercussions and the economic structure: an input-output approach. The review of economics and statistics, 262-271.

Miketa, A., & Mulder, P. (2005). Energy productivity across developed and developing countries in 10 manufacturing sectors: patterns of growth and convergence. Energy Economics, 27(3), 429-453.

Miller, R. E., & Blair, P. D. (2009). Input-output analysis: Foundations and extensions, second edition. Input-Output Analysis: Foundations and Extensions, Second Edition. https://doi.org/10.1017/CBO9780511626982

Mukherjee, K. (2008). Energy use efficiency in US manufacturing: A nonparametric analysis. Energy Economics, 30(1), 76-96.

Nakano, S., Arai, S., & Washizu, A. (2018). Development and application of an inter-regional input-output table for analysis of a next generation energy system. Renewable and Sustainable Energy Reviews, 82, 2834-2842.

National Academy of Sciences, National Academy of Engineering, and N. R. C. (2009) America’s Energy Future. doi: 10.17226/12091.

US EPA. (1999). Inventory of US greenhouse gas emissions and sinks: 1990–1997.

Palmer, G. (2017). An input-output based net-energy assessment of an electricity supply industry. Energy, 141, 1504-1516.

Pan, L., Liu, P., Li, Z., & Wang, Y. (2018). A dynamic input–output method for energy system modeling and analysis. Chemical Engineering Research and Design, 131, 183-192.

Park, Y. S., Egilmez, G., & Kucukvar, M. (2015). A novel life cycle-based principal component analysis framework for eco-efficiency analysis: case of the United States manufacturing and transportation nexus. Journal of Cleaner Production, 92, 327-342.

Park, Y. S., Egilmez, G., & Kucukvar, M. (2016). Emergy and end-point impact assessment of agricultural and food production in the United States: a supply chain-linked ecologically-based life cycle assessment. Ecological indicators, 62, 117-137.

Pelletier, N., Pirog, R., & Rasmussen, R. (2010). Comparative life cycle environmental impacts of three beef production strategies in the Upper Midwestern United States. Agricultural Systems, 103(6), 380-389.

Phylipsen, G. J. M., Blok, K., & Worrell, E. (1997). International comparisons of energy efficiency-Methodologies for the manufacturing industry. Energy policy, 25(7-9), 715-725.

Ramanathan, R. (2005). An analysis of energy consumption and carbon dioxide emissions in countries of the Middle East and North Africa. Energy, 30(15), 2831-2842.

Scott, R. E. (2015). The manufacturing footprint and the importance of US manufacturing jobs. Economic Policy Institute, 22.

Sembill, D., & Dreyer, K. (2009). Granting time–Restricting time–Wasting Time? Subtle patterns in vocational schooling. In VET Boost: Towards a Theory of Professional Competencies (pp. 233-244). Brill Sense.

Shafiee, S., & Topal, E. (2009). When will fossil fuel reserves be diminished?. Energy policy, 37(1), 181-189.

Sözen, A., & Alp, İ. (2009). Comparison of Turkey's performance of greenhouse gas emissions and local/regional pollutants with EU countries. Energy Policy, 37(12), 5007-5018.

Sherman, H. D., & Zhu, J. (2006). Data Envelopment Analysis Explained. Service Productivity Management: Improving Service Performance using Data Envelopment Analysis (DEA), 49-89.

Su, B., & Ang, B. W. (2014). Input–output analysis of CO2 emissions embodied in trade: a multi-region model for China. Applied Energy, 114, 377-384.

Sun, X., Li, J., Qiao, H., & Zhang, B. (2017). Energy implications of China's regional development: New insights from multi-regional input-output analysis. Applied energy, 196, 118-131.

Talluri, S., & Yoon, K. P. (2000). A cone-ratio DEA approach for AMT justification. International Journal of Production Economics, 66(2), 119-129.

U.S. Energy Information Administration (2018) Nonrenewable Energy Sources. Retrieved from https://www.eia.gov/energyexplained/?page=nonrenewable_home.

U.S. Energy Information Administration (2018, May 29) Use of Energy in the United States. Retrieved from https://www.eia.gov/energyexplained/index.php?page=us_energy_use.

U.S. Energy Information Amministration (2017) ‘EIA Outlook 2013’. doi: www.eia.gov/forecasts/ieo/pdf/0484(2016).pdf.

US Energy Information Administration (2013) ‘Electric Power Annual 2017’. Retrieved from https://www.eia.gov/electricity/annual/pdf/epa.pdf (October 2017).

US Energy Information Administration (2017, April 30) ‘Use of Electiricty - Basics’. Retrieved from https://www.eia.gov/energyexplained/print.php?page=electricity_use.

US Energy Information Administration, (2017), U.S. primary energy consumption by source and sector in 2017. Retrieved from https://www.eia.gov/electricity/annual/pdf/epa.pdf

Vázquez-Rowe, I., Villanueva-Rey, P., Iribarren, D., Moreira, M. T., & Feijoo, G. (2012). Joint life cycle assessment and data envelopment analysis of grape production for vinification in the Rías Baixas appellation (NW Spain). Journal of Cleaner Production, 27, 92-102.

Westermann, G. (Ed.). (1999). Data envelopment analysis in the service sector. Deutscher Universitäts-Verlag.

Wiebe, K. S., Bruckner, M., Giljum, S., & Lutz, C. (2012). Calculating energy-related CO2 emissions embodied in international trade using a global input–output model. Economic Systems Research, 24(2), 113-139.

Wiedmann, T. (2009). A review of recent multi-region input–output models used for consumption-based emission and resource accounting. Ecological Economics, 69(2), 211-222.

Wiedmann, T., Wilting, H. C., Lenzen, M., Lutter, S., & Palm, V. (2011). Quo Vadis MRIO? Methodological, data and institutional requirements for multi-region input–output analysis. Ecological Economics, 70(11), 1937-1945.

Wu, X. F., & Chen, G. Q. (2017). Energy use by Chinese economy: A systems cross-scale input-output analysis. Energy Policy, 108, 81-90.

Xia, X. H., Chen, B., Wu, X. D., Hu, Y., Liu, D. H., & Hu, C. Y. (2017). Coal use for world economy: Provision and transfer network by multi-region input-output analysis. Journal of cleaner production, 143, 125-144.

Yang, Y., Heijungs, R., & Brandão, M. (2017). Hybrid life cycle assessment (LCA) does not necessarily yield more accurate results than process-based LCA. Journal of Cleaner Production, 150, 237-242.

Zhang, B., Chen, Z. M., Xia, X. H., Xu, X. Y., & Chen, Y. B. (2013). The impact of domestic trade on China's regional energy uses: A multi-regional input–output modeling. Energy Policy, 63, 1169-1181.

Zhang, B., Qiao, H., Chen, Z. M., & Chen, B. (2016). Growth in embodied energy transfers via China's domestic trade: Evidence from multi-regional input–output analysis. Applied Energy, 184, 1093-1105.

Zhang, Y., Zheng, H., Yang, Z., Su, M., Liu, G., & Li, Y. (2015). Multi-regional input–output model and ecological network analysis for regional embodied energy accounting in China. Energy Policy, 86, 651-663.

Kadhim Abbood (2016) Multi-region Input-Output-based Carbon and Energy Footprint Analysis of U.S. Manufacturing. (Unpublished master`s thesis), University of New Haven, West Haven, CT.